

Family Microsimulation (FAMSIM): Socio-economic Analysis, Simulation and Surveys

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working paper



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"FAMILY MICROSIMULATION"

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I. The role of microsimulation in family studies	3
General trends in social sciences	3
The human life course	5
Description of the life course.....	6
Microsimulation approaches, traditions and models	7
Strengths and advantages of microsimulation models	11
II. Technical approaches to microsimulation.....	14
Discrete and continuous time approaches to dynamic microsimulation	14
Open and closed populations and samples	15
Surveys and data used as sources for MSMs	15
Longitudinal surveys	15
Cross-sectional surveys	16
Aggregated Data	16
Modeling state durations and transitions	17
Describing transitions and durations of states	17
Commonly used distributions for outlining the hazard	18
Regression models for estimating transition probabilities.....	19
Cohort-component methods.....	20
Statistical matching.....	20
III. The FAMSIM prototype	22
Characteristics of FAMSIM	23
Variables and transitions	24
The FAMSIM Software	27
Estimation results: Examples.....	31
First pregnancy leading to birth.....	31
Second pregnancy leading to birth	32
Third pregnancy leading to birth	33
Fourth and further pregnancies leading to birth	34
Partnership formation.....	35
Dissolution of partnership	38
Simulation Results	41
Simulation results for partnership forms: 2000 and 2010	43
Simulation results for number of children: 2000 and 2010	44
IV. Outlook: the FAMSIM+ project	45
Education.....	45
Fertility	45
Migration	46
Partnership formation and dissolution.....	47
Income and labor market participation.....	47

Consumption and savings	48
Family policies.....	49
References.....	51
Appendix I – Logits	54
Appendix II – Microsimulation Projects	58

I. The role of microsimulation in family studies

Family studies try to shed light on a variety of questions and topics regarding the ways in which people organize their lives and social relations. This also holds true for the relation between individual action and social dynamics. The methods used vary widely as do the research disciplines involved. The term ‘family’ specifies branches of various research disciplines (e.g. psychology, sociology, economics, history, demography, law) and areas in politics. The rapid social and demographic changes in the last decades also raise a number of crucial policy questions: How can we finance the social security system in an ageing society in the long run? What must family policies look like in order to be able to cope with the increasing variety of individual and family lifestyles? Therefore, the economic and behavioral assessment and the evaluation of family policies constitute an important field in family studies.

The massive social and demographic change in the last decades went hand in hand with tremendous technological progress, with computers now being a powerful and indispensable tool in various fields of research. Their ability to process large amounts of data has boosted data collection, enabled new survey designs and ways of data analysis. Moreover, the availability of powerful computers has led to new methods of theory development and testing by agent-based computer simulation. Another line of computer simulation is microsimulation based on statistical models of behavior. This method is widely used in policy analysis. In general, the impact of massive social change on people’s lives has become a vital area of research, and great progress has been made in the ways of studying how lives change over time. Methodological issues in life-course and family studies increasingly share in a new paradigm, the so-called ‘life-course paradigm’. It combines several major theoretical and empirical streams of research, connecting social change, social structure, and individual action. (Giele 1998)

General trends in social sciences

As family research involves a variety of research disciplines, it is not only influenced by general changes and shifts in the focus of attention, but also benefits from their development. This is especially true in the field of social sciences, where a comprehensive change can be observed along four dimensions: (Willekens 1999)

- from structure to process
- from macro to micro
- from analysis to synthesis
- from certainty to uncertainty

The change from structure to process shifts the focus of attention from a static view of social systems to the dynamics of systems over time and the processes generating the dynamics. While this “transition from entity-oriented perception of reality to process-oriented perception” was made by nearly every social and natural science (Willekens 1999; 4), its importance increases with the speed of the observed social and demographic changes and the various new questions raised by these changes. The focus on processes brings in various new concepts, with causality and time being among the most important. Various phenomena regarding families are characterized by their rapid change over time, and substantial research effort is required to identify and understand the underlying processes generating them. Good examples are low fertility, increasing divorce rates and changes in the distribution of income and wealth in general or between people with and without children. The importance of time is increasingly recognized in the field of policy analysis, where the attention shifts to the long-term dynamics and the sustainability of such systems as tax-benefits or social security. In studying distribution effects of policies, time adds a new dimension to research, as distribution effects are not only analyzed in a cross-sectional view for a given time, but also over time, between cohorts and over generations.

Family research mainly focuses on the micro units of society—people in their closest kinship context—applying a variety of research methods and involving a wide range of disciplines. Consequently, the range of research questions that are addressed is wide, with ‘family relevance’ constituting the smallest common dominator. Family relevance not only reduces the number of phenomena that need to be studied, but somehow also defines the viewpoint: disaggregated social and economic processes and dynamics. When investigating the behavior of socio-economic systems, family research therefore mainly concentrates on processes inherent in the system and its agents: individuals and families. This micro viewpoint is growing in importance in all social sciences that tend to move from macro to micro explanations and to interpret changes on the macro level as results of actions taken by individual agents and their interactions. These interactions also include reactions and feedback of individual agents in connection with changes in their environment, i.e. changes on the macro level that form the context of individual decisions and actions.

When shifting the focus of attention from structure to process, research increasingly tends not to stop at the analysis of these processes and the resulting structures. The identification of the elementary processes that generate the complex dynamics of a system are indispensable for understanding these dynamics, but also have to be ‘put together’ by way of synthesis. This way, system dynamics can be projected under different assumptions. As described in the next chapter, the life course may be viewed as being a combination of a large number of elementary processes. The challenge is to detect the elementary processes and the rules that link them. Microsimulation is the main tool for linking multiple elementary processes in order to generate complex dynamics and to quantify what a given process contributes to the complex pattern of change.

Another shift in social sciences is based on the insight that uncertainty is associated with many events. Agents have only limited control over most events and their exact timing. Hence the individual likelihood that certain events will or will not happen becomes an important issue. This holds true for many phenomena and events studied in family research: pregnancy is a good example. While the degree of planning might vary, the exact timing cannot be controlled though probabilities might be well known. The probabilistic view adds a new quality to any kind of forecasts, as the investigated dynamics include both the most likely outcome and the probabilities of this outcome.

The afore mentioned four shifts can be observed in varying degrees in different social sciences. They have a huge impact on the way in which individual lives and interactions of individuals are described and investigated. In the course of time, these important paradigmatic shifts led to the development of the human life course as a central concept or ‘organization principle’.

The human life course

The term ‘life course’ was first used by Cain (Cain, 1964) to encompass anthropological, sociological, and psychological concepts of aging, particularly as they were related to the maturing individual's movement through an expected sequence of social roles. The life course refers to a sequence of socially defined events and roles that the individual enacts over time. It differs from the concept of life cycle in allowing for many diverse events and roles that do not necessarily proceed in a given sequence but that constitute the sum total of persons' actual experience over time. (Elder, 1975) These roles and the transitions from one role to another are central issues in family research: childhood, partnership formation and dissolution as well as parenthood, just to name some of them. Contrary to life-cycle concepts that are widely used, for example in economics or psychology, and are based on a predetermined ‘typical’ sequence of roles, episodes of life or expected behaviors, the life course concept permits us to study changing role patterns and the interactions between different domains or such careers as education, jobs, partnerships and births. The individual life course is determined by four key factors that make up the key elements of the life course paradigm:

- location
- social integration
- goal orientation and
- strategic adaptation

The location in time and place or the cultural background constitutes the first key element. It determines the individual life course and closely corresponds to period effects, a demographic concept frequently applied in historical demography. Using archival parish registers, births, deaths and marriages are reconstructed and the economic and political factors

that shaped the key demographic events of everyday life are determined. Key topics and insights of this kind of historical research—which concentrates on ‘ordinary people’ rather than leaders and battles—regard the changing roles and functions of families, and in particular women. In addition, institutional changes caused by demographic changes (e.g. changes in inheritance laws) are investigated.

The second key element is social integration or the concept of ‘linked lives’. It closely corresponds to cohort effects as used in demography. Important insights were gained by comparing and identifying ‘typical’ life patterns of different cohorts, a method widely used in sociology. Rich, new empirical studies of variations in life patterns among different birth cohorts helped to elaborate the multidimensional model of the human life course.

Individual age is of key importance in all life-cycle models, especially in the psychology of developmental stages. Various scholars have tried to describe the typical life cycle that begins with birth and moves through adolescence, young adulthood, and the middle years to old age and death. By moving to a multidimensional model, the study of the life course has perceivably moved from a tendency to divide the study of development into discrete stages to the firm recognition that any point in the life span must be viewed dynamically. It must be seen as the consequence of past experience and future expectation, as integration of individual motives and external constraints. In this way, human agency and individual goal orientation are added to the explanatory framework.

The fourth component of the life course framework was mainly brought in by longitudinal surveys and associated methods: strategic adaptation or the timing of lives. Timing of life events can be understood as both passive and active adaptation for reaching individual or collective goals. By using duration-dependent rates of changes for characterizing different persons in a population, and by differentiating between endogenous, exogenous and reciprocal effects we can distinguish the impact of biological change (age grade) from the impact of socialization and experience (event grade) or cultural and institutional change (history grade). Individuals adapt to the challenges confronting them by timing the events of their lives so as to make the most of opportunity and suffer the least frustration and failure. Whatever a person’s social and cultural heritage, friendships and networks, or personal motivation, all come together and are experienced through the individual’s adaptation to concrete situations and events. (Giele 1998; 10)

Description of the life course

While human lives may be—and actually are—described in various ways and terminologies, one approach increasingly gains importance and dominates life descriptions from a life course perspective: the description of lives as event histories. An event is defined as qualitative change that occurs at a specific point in time and that places an individual in a new status. Events are transitions between states such as marriage and divorce that change the

marital status of a person. Individuals experience events and organize their lives around these events. As Willekens (1999: p 2) states, most people spend a considerable part of their life either preparing for life events or coping with life events.

States and events typically belong to different domains or careers, like partnership, job and educational careers that interact and influence each other. As a result, people may experience problems of synchronization and compatibility of careers. Many of the resulting problems—e.g. the reconciliation of job and family life—are central in family studies. A typical strategy to cope with incompatibilities is rescheduling activities and events. An example of this strategic adaptation is to postpone births.

The collection of all possible states for each career to be considered in a specific analysis creates a state space that determines all possible trajectories and outcomes of individual live histories along with all possible transitions. Once defined, the description of individual lives consists of ‘event history data’, i.e. all events are recorded together with the time they occurred or alternatively, all states are recorded by precisely noting when they began and when they ended.

The FAMSIM model—to be presented in more detail later in this paper—is based on this kind of history event data collected in the Family and Fertility Survey (FFS). In this model, events belong to four distinguished careers: education, work, partnerships and births. While the FFS data allow the generation of individual biographies or event-histories in a series of important family-related events, FAMSIM—and microsimulation models in general—can be viewed as a way to predict the future course of individual biographies. At this point, microsimulation enters the field, usually divided into two main traditions: data-driven and context-driven microsimulation.

Microsimulation approaches, traditions and models

In this paper, I will use a broad definition of both, simulation and microsimulation. In this way, microsimulation covers a broad range of models, from static tax benefit models to dynamic databased microsimulation and context-driven, agent-based simulation rooted in the artificial intelligence approach. In line with this broad view, simulation cannot be exclusively envisaged as a technique that, in principle, does not ‘add’ anything to models. This view is predominantly found in economics and in data-driven microsimulation that clearly distinguishes between the model as such and the technique used to ‘run’ or ‘solve’ the model. However, this distinction cannot be made in agent-based simulation where (computer) simulation constitutes a particular type of modeling and simulation serves not only as technique to ‘solve’ and ‘run’ a model, but also as a method of theory development.

What all microsimulation approaches and traditions have in common is an analysis of the behavior of a system based on characteristics of the micro units distinguished in the system. These are changed or autonomously change according to a behavioral model. The main idea

of microsimulation is that the best way to explain processes resulting from the actions and interactions of a large number of micro units is to look at the micro units and their behavior. One can expect to find more stable behavioral relationships on the micro level than in aggregated data. These are influenced by structural changes when the number or size of the micro units in the population changes, even though the behavior of the individual micro units and their individual characteristics do not change. These micro units might be particles moving in line with probability laws, e.g. in fluids or thermodynamics, the field where microsimulation was first introduced. They might also represent artificial species of ‘artificial societies’ as is the case in most agent-based simulations. But they can also represent individuals, families or households of empirical populations, as it is the case in ‘data-based’ microsimulation.

In ‘data-based’ microsimulation, the main distinction is between static and dynamic microsimulation models. Both are based on micro databases usually storing detailed individual, household and (regional) environmental attributes. In economic modeling, the main difference as compared to other kinds of analysis is the way these micro data are used. They are of central importance in tax and benefit analysis, as policies usually link taxes and benefits to several individual and household attributes in a nonlinear fashion. For this reason, traditional methods of estimating welfare costs and the distribution of benefits by means of some aggregate functions are not suitable for this kind of analysis.

Reduced to its essentials, a microsimulation model suitable for this type of policy evaluations consists of two parts (Martini 1997):

- a baseline database: a data set containing information on individual or family/household units, in particular socio-demographic characteristics and economic information that is related to a set of policies.
- a set of accounting rules: these are computer language instructions that produce the provisions of existing or alternative tax and transfer systems or other relevant institutional features for each unit.

In the early days of microsimulation, constructing representative data sets with all necessary variables and modeling at least part of a complex tax-benefit system absorbed all the resources. The work carried out by Pechman and Okner (1974) to analyze the redistributive effects of the US tax system represents the most celebrated example of this type of research. Generally, these models can be characterized as static, as they work with a given datasheet of micro data, using only methods of ‘static aging’ by re-weighting the dataset to maintain representativity for society over time. In addition, some microsimulation models comprise a third component, a set of behavioral relationships that varies greatly in scope and importance across models. There are two types of behavior:

- behavior that results in events which take place over time, e.g. demographic events, (marriage, divorce, deaths etc.) and economic events (e.g. finding a job), and

- behavior producing feedback of individuals and/or families reacting to changes in external circumstances, notably to changes in public policies.

Historically, microsimulation moved from a description of the distributional impact of the existing tax and transfer system to a second stage, in which it became a tool for understanding the impact of alternative proposals for reforming existing systems, with or without accounting for behavioral response. A more recent example is the analysis of the way the family is treated in income tax systems across Europe by O'Donoghue and Sutherland (1999). In this study, different European tax systems were examined for the UK, using the tax-benefit microsimulation model POLIMOD.

To obviate the limitations of static models, a second important development led to the construction of dynamic models, which can be used to compare the effects of alternative policies many years into the future. The study of the evolution of retirement systems, and the evaluation of alternative arrangements to finance public and private pension systems are typical applications of dynamic microsimulation models of this type. Again, the use of micro-data is of central importance in this kind of detailed analysis. This holds especially true for the calculation of retirement income, where required attributes often not only include the full individual's contribution history but also the spouse's history. Examples of existing models of this type explicitly designed to study policy options in the field of social security and pension systems are DESTINIE (Bonnet 1999) developed in France and the Canadian DYNACAN** model.

Time is one of the most important concepts in databased dynamic microsimulation and adds a new dimension to this kind of analysis, allowing us to study distributional aspects of policies not only at one given moment but also over time and generations. This way, dynamic microsimulation simultaneously addresses aggregate, distributive and longitudinal or 'life path' issues, allowing for a long-term view. This makes it a powerful and flexible tool especially in policy analysis. In this type or 'tradition' of microsimulation, individual characteristics are changed by a dynamic process generated by a combination of deterministic and stochastic elements. The behaviors of individuals are functions of individual, household or socio-economic characteristics. They are usually included in discrete choice models as independent variables or simply as categories used to estimate transition matrices that describe the probability of moving from one state to another. This kind of dynamic modeling was first introduced in 1956 by Guy Orcutt's DYNASIM (Orcutt 1957) model for the US. It was very popular in a variety of fields. Its development was supported by the enormous progress in electronic storage capacity, the increasing availability of longitudinal micro –data, and improved of statistical methods, especially in the field of longitudinal research and event history analysis.

** An annotated list of all microsimulation projects quoted in this paper is contained in the Appendix II.

By introducing time, dynamic microsimulation permits us to simulate dynamic feedback between individual characteristics and those on the population level. This is explicitly done in multilevel models that simultaneously handle the micro scale of people and the macro scale of contexts within one model. In the multilevel modeling technique, each individual evaluates his or her environment as an entity and reacts to it, changing the environment by his or her behavior. In practice, detailed micro-models and macro outcomes are not always produced in a single model, but micro-macro links are established in order to connect micro with macro-models. An example of this approach is the Darmstädter Mikro-Makro-Simulator (DMMS) that links a micro model of the household and enterprise sector with a macro model of the whole economy. This permits us to study the feedback between the two levels. Another method that is widely used (and disputed) are aligning techniques that ‘force’ micro models to fit to externally determined macro scenarios.

As mentioned above, this type or tradition of microsimulation permits a clear distinction between data representing the population, the model that determines behavior, Monte Carlo simulation—usually used to ‘run’ the model—and the software necessary for the whole exercise. Micro-econometric and statistical models tend to be associated with this type of microsimulation, with behavior usually being expressed in transition probabilities or duration times. According to the way of modeling time as such, we can distinguish two main approaches: (1) the continuous-time competing-risk approach to dynamic microsimulation modeling, and (2) approaches based on a discrete-time framework. For a comprehensive comparison of associated statistical models, data requirements, necessary assumptions, advantages and drawbacks see Galler (1998)

The second microsimulation ‘tradition’ is context-driven microsimulation or agent-based simulation based on the distributed artificial intelligence approach. Micro units are ‘intelligent’ and acting agents. They have goals and obey rules. The following features are typical for agents:

- agents have receptors, they get input from the environment
- agents have cognitive abilities, beliefs and intentions
- agents can follow different rules and decide which rules to follow
- agents live in groups of other agents and interact
- agents can and do act simultaneously
- agents can learn

Agent-based simulation differs from data-driven microsimulation in two essential ways: (1) the ‘rules of motion’ or behavioral model is not based on statistical modeling relying on empirical data, but works on the basis of rules and ‘intelligent’ behavior, and (2) the pursued aim: context-driven microsimulation is not primarily intended to forecast the behavior of empirical populations. It was designed to study dynamics and patterns of artificial societies

resulting from the interactions of artificial species that follow certain rules. By ‘growing’ these societies, simulation serves as a tool to develop and test theories that might help to explain human behavior, because artificial societies might show similar behavioral patterns as empirical ones.

While both of these ‘traditions’ or approaches have evolved in almost total ignorance of each other (Troitzsch 1996; v), both increasingly use each other’s concepts, and a synthesis might be brought about by combining or permitting various ‘rules of motions’ and population types in line with the research questions and goals. Defined in this way, microsimulation can be used both for theory testing and for forecasting. It has the potential to improve the accuracy of economic forecasting and to provide new insights into underlying economic principles.

Strengths and advantages of microsimulation models

One of the central strengths of microsimulation is the fact that it can include more variables than other methods. This is especially important when it is used as a projection and planning tool. For example, when trying to estimate such future demands as the one for health care facilities on the basis of population projections, a large set of household characteristics (e.g. household size, family composition, age and income) can be included. This feature distinguishes it from existing macro-level projections of future population trends. Besides breaking down the population by age and sex, such projections can only add a very limited number of variables to the analysis. Projections that are useful for analyzing different, population-related social and economic research must consider additional dimensions. Some examples are education, human capital development, rural/urban differences, household structures and family networks, which become increasingly important in the context of rapid demographic change.

Being based on micro units, microsimulation avoids bias caused by aggregation, because it allows us to construct the appropriate behavioral models at the level at which the relevant decisions are made, i.e. the micro level. For the same reason, there is no need to translate behavioral relations taking place at the micro level to the macro level. This also implies that no information is lost through aggregation as it is always possible to disaggregate both the model structure and the results that are derived from the model.

From a policy-maker’s viewpoint, the main strength of microsimulation is its ability to provide an anticipatory evaluation of certain policies. This permits us to test new policies in a virtual world to prevent unintended social side effects. In other words, microsimulation allows to test and fine-tune planned policies or policy changes in a ‘virtual world’ before introducing them in real societies. The dimensions added to more traditional policy evaluations are the possibility to address distributional aspects in both a ‘static’ cross-sectional way and over time.

As microsimulation is based on micro data, it allows flexible aggregation, because the information may be cross-tabulated in any form, while schemes are predetermined in aggregate approaches. Simulation results can be displayed and accounted simultaneously in various ways, i.e. as aggregate time series, cross-sectional joint distribution, and person and family life paths. Flexible aggregation helps to determine the ‘winners and losers’ of policy changes. An example is the possibility to study and compare contribution and benefit histories over the entire individual lifespan, i.e. by calculating the internal rates of returns of social security distributions by age cohorts. In this way, microsimulation can serve as powerful tool in the study of various aspects regarding population balance. (Lutz, Sanderson 2001)

Using such multivariate approaches as history-event analysis or rule-based behavioral models, microsimulation lets us study the interaction between variables and the life course interactions between various parallel careers and roles (e.g. education, work, partnership and parenthood) within a changing socio-economic context.

Modeling the behavior of individuals, these micro units may be rearranged to produce different higher-level population structures. In this way, observations of populations may be situated within the larger context of what could be possible. This approach constructs aggregates from simple components selected from a finite repertoire. These are combined according to a system of rules. While modeling takes place on the individual level, microsimulation allows us to study the processes resulting from the interaction between the micro units. In addition, microsimulation can be used to determine the contribution of individual processes to the complex dynamics and patterns of changes on the macro level. Using models to compose complex processes from simple ones has been termed ‘theoretical modeling’ (Burch, 1999, p. 4) as opposed to ‘empirical modeling’, which works with a specific data set. The empirical, ‘data-based’ tradition mainly uses the possibility to study the interaction between individuals by microsimulation to study changes in family and kinship networks. Direct applications can be found in the field of elderly care and other aspects of ageing societies, where the knowledge of the detailed household and family characteristics constitutes a valuable source of information for policy design. The knowledge of kinship-patterns also permits us to study intergenerational transfers and bequests in detail.

The potential to handle large state spaces offers the possibility to include not only a wider set of individual characteristics and categories, but also spatial and other environmental characteristics. This allows detailed modeling and the study of the interaction between individuals and the environment. The study of these interactions is of key importance in most agent-based and multilevel microsimulation models.

When stochastic elements –(i.e. Monte Carlo simulation) are included in microsimulation, the outcome differs for each simulation experiment. This permits us to explore the distribution of events rather than making point –estimates. Consequently, uncertainty and risk are represented more adequately. Considering all the advantages outlined above, it does not come as a surprise that they are in high demand, in particular as policy researchers have no

alternative modeling strategy to address a series of related, critical policy and research issues. Caldwell and Morrison (2000) give the following examples:

- analyzing projected winners and losers on a period-specific or lifetime basis
- simultaneous analysis of families and individuals
- exploring the way social security programs work at the micro-level in the context of the broader tax/transfer system
- quantifying incentives to work, save, or retire at particular life course or period junctures
- cross-subsidies across population segments or cohorts
- feedback effects of government programs on population demographics, and
- longer-term consequences of social trends in marriage, divorce and fertility.

Responding to the demands associated with prospective social security and welfare reform in the context of demographic change, decision-makers of various countries –(among them the US, Canada, France, Norway, The Netherlands, Germany, Sweden and Australia) have started to use dynamic microsimulation models to supply key-policy inputs. Prominent examples of microsimulation models used in the field of policy research are CORSIM in the US, DYNACAN in Canada and DESTINIE in France, MOSART in Norway, NEDYMAS in the Netherlands, SVERIGE in Sweden (Vencatasawmy 1999) and DYNAMOD in Australia.

II. Technical approaches to microsimulation

Microsimulation uses a wide variety of statistical and econometric methods. This section will first give an overview of the most common methods and then focus on methods mainly used in discrete time microsimulation models relying on longitudinal event data.

Discrete and continuous time approaches to dynamic microsimulation

In general, two types of model structures are used: The first type comprises continuous time models that focus on the ‘real’ duration between transitions. Beginning at a fixed starting point, a random process generates events that can take place at any point of time throughout the simulated period. This process is based on a probability density function determined by an empirical distribution within every cohort. It may also be based on a set of explanatory variables that were identified by selected regression techniques. The event occurring next to the starting point is then simulated. The point of time at which this event happens becomes the new starting point. The procedure is repeated until the event ‘death’ of the simulated individual occurs.

The second type of discrete time models determines the states and transitions for every time period, while disregarding the exact points of time within the interval. Transitions are usually modeled as probabilities conditional on the previous state (univariate form) or as probabilities related to the previous state(s), to exogenous variables and the (quasi absolute) time index, as well the state durations and repetitions. Instead of taking state durations from a continuous distribution function determining when an event happens and a new state is reached, a Bernoulli distribution is employed to determine whether a certain event takes place within the simulated period. Events are assumed to happen just once in a time period. Some attention should be drawn to the fact that, in reality, several events can take place within one discrete time period, but just one event can be recorded. To solve this problem, either every possible combination and succession of events within a time period has to be assigned to an artificial event and its conditional probability has to be computed from the probabilities of the elementary events, or an exclusive competing risk model has to be employed. If an exclusive competing risk approach is used within a discrete-time model, the probabilities for transitions are calculated for every period, and transitions with a probability below the specified critical rate are eliminated. Then the sequence of the remaining transitions is generated either randomly or following a predefined order. Subsequently, the first transition is chosen, all other possible transitions for that period are eliminated. Other transitions may be disregarded or be shifted to the next or previous period, where no event has taken place. The chance of finding a ‘free’ period among the calculated periods increases with shorter intervals.

From a theoretical point of view, continuous models are more efficient, because they are more straightforward in handling competing risks. When introducing time-dependent

covariates (e.g. stock variables – aggregated deposits and loans – or flow variables – annual income and consumption), these apparently manageable models become quite difficult to handle. Moreover, when compared with discrete time models, the data requirements are huge. For this reason, discrete time structures are often a favored option.

Open and closed populations and samples

In a closed population, interactions can only take place between the agents belonging to the monitored population. The population merely changes by births and deaths of agents. In an open population, the interaction range is extended to agents belonging to other groups. The monitored population also changes due to migration.

While the theoretical formulation is quite clear, this cannot be said regarding some practical implications for microsimulation (simulating samples rather than whole populations). When modeling MSMs on a closed sample, all interactions (especially such processes as partner matching) can only happen within the sample. Agents from outside the sample who interact with individuals within the dataset have to be created artificially. As in the case of immigrants within the whole population, these agents have to be created ‘ex nihilo’. To do so, we need at least the characteristics required to simulate the sampled individuals. If the interaction with a sampled person takes place for a longer interval, e.g. marriage, these outsiders should be included in the sample, and all characteristics of the simulated agents have to be imputed.

Surveys and data used as sources for MSMs

The data sources used for MSMs may be of various kinds. A rich database is needed for raising the starting population; some information from other sources can be implemented while formulating and executing the MSMs.

Longitudinal surveys

In MSMs, (quasi)longitudinal data are essential for building the starting population and for determining the parameters used in the behavioral equations for one sample. However, several caveats need to be considered. When using household panels, it should be noted that the sample of reporting households changes over time. This does not matter in the macro view, but is detrimental to the formulation of behavioral equations in microsimulation. If household A (that reported for some 10 years) is replaced by household B (whose characteristics are mainly comparable), the simulation is reduced to the comparative characteristics. In the long run, this gradually reduces the advantages of microsimulation as compared to usual macro simulation methods.

In general, the registry data presumably available for every individual (e.g. social security data) are good and reliable data sources. As these data sources tend to be exclusively used by administrative authorities, research institutes can often just use published parts of the existing information to impute missing data. The main question here is whether or not the information

can be linked. In many countries, the data protection laws even forbid different administrative authorities to make such a connection. If the registry data can be connected to the surveyed persons/households, these data sources can be quite useful.

A very interesting data source is generated by retrospective history event surveys. It should always be kept in mind that the data obtained from this kind of surveys are subject to individual preferences. Event X_1 in state Y_1 can be viewed as very important for individual A_1 but irrelevant for individual A_2 . Thus, it will be reported by A_1 , but perhaps not mentioned by A_2 . The obtained data are based on a rather subjective point of view. These mnemonic-censored data produce effects comparable to those created by quantitatively censored data, but the causes of the truncation by memory are much more diverse. Besides, only few approaches for handling these truncations have been developed so far. The main events of life history (e.g. marriages, childbearing, first autonomous change of residence etc.) are less subjective. Within history event data, one crucial weakness arises: life history data are *per se* censored by the survivors. Disregarding this fact, this may give rise to some biased inferences. The last transitions at the end of a life are usually not represented adequately within history events data.

Cross-sectional surveys

Longitudinal surveys usually have few variables within the data set; cross-sectional data are commonly used to compensate this fact. Cross-sectional surveys have little relevance as sole data source of a MSMs project. However, cross-sectional data from specialized surveys and micro census surveys may be used to fill in information gaps regarding several exogenous variables. Additionally, the information contained in the general census constitutes the basis for extrapolating the MS results to the whole population and for constructing the starting population of MSMs.

Aggregated Data

In multivariate MSMs, several macro variables have to be used as exogenous variables in order to compensate for the lack of representativity of the model structure. For example, if the MSMs simulate the labor supply of households, certain influences governing the demand of labor cannot be simulated. For this reason, such macro variables as the (lagged) consumer demand, shifts in investment and interest rates, variations in net export, seasonal variations etc. can serve as controls for changes in the demand of labor in the respective industries.

Modeling state durations and transitions

State durations and transition probabilities are generated from existing data and/or follow general assumptions. Once the probabilities and the sequence of all transitions treated within the MSMs have been stated, the state durations can be simulated using Monte Carlo procedures.

Describing transitions and durations of states

Duration models describe the probability of the lengths of defined states. The quit rate describes the probability of a transition that changes the state within the time interval (resp. before the end of the interval t_0)

$$[0.1] \quad q(t) = \Pr(t < t_0) = F(t_0); q \in (0;1),$$

while the survivor rate describes the opposite probability of maintaining the state for the same time span

$$[0.2] \quad s(t) = \Pr(t > t_0) = 1 - q(t_0) = 1 - F(t_0); s \in (0;1)$$

The conditional survivor rate describes the probability of remaining in a certain state for more than $t_0 + \Delta t$.

$$[0.3] \quad s(t, t_0) = \Pr(t_0 + \Delta t < t \mid t > t_0) = \frac{1 - F(t_0 + \Delta t)}{1 - F(t_0)}$$

Finally, the most important statistic in MSMs, i.e. the hazard rate, describes the conditional probability of quitting a state in which the monitored person has been for a certain time interval.

$$[0.4] \quad \begin{aligned} h(t) &= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \Pr(t + \Delta t > t \mid t > t_0) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \frac{\Pr(t + \Delta t > t)}{\Pr(t > t_0)} \\ h(t) &= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \frac{F(t + \Delta t) - F(t)}{1 - F(t)} = \frac{f(t)}{1 - F(t)} = - \frac{d(\ln(1 - F(t)))}{dt} \end{aligned}$$

The hazard rate can be used to comprehensively describe the distribution of the lifespan within a state ($s(T)$) and the failure density ($f(T)$). Therefore, it is a most suitable key element for calculating essential probability measures.

$$[0.5] \quad \begin{aligned} \ln(1 - F(T)) &= - \int_0^T h(T) dT; T \equiv T[t_0, t] \\ s(T) &= 1 - F(T) = \exp\left(- \int_0^T h(T) dT\right) \\ f(T) &= s(T)h(T) = h(T)\exp\left(- \int_0^T h(T) dT\right) \end{aligned}$$

Commonly used distributions for outlining the hazard

The hazard is empirically determined by several techniques. In most cases, the calculated hazard rates are insufficient and often biased for calculating all hazard rates over the maximum time span of a state. Instead, some standardized distribution functions are used to describe the entire path of the hazard or the survivor function respectively. The two functions most frequently cited in literature are the exponential distribution and the Weibull distribution.

The exponential distribution can be used for modeling the lifespan of systems that do not age. Of course, the individuals modeled within MSMs are subject to an ageing process, but there are some transitions that clearly do not depend on the age of the individual or the duration of the current state. The simplest form of the exponential function is characterized by a distribution function

$$[0.6] \quad F(t) = 1 - \exp(-\lambda t) = q(t)$$

or a density function $[0.7] \quad f(t) = \lambda \exp(-\lambda t)$.

As the total as well as the conditional survivor rate is

$$[0.8] \quad s(t) = s(t, t_0) = \exp(-\lambda t),$$

the hazard rate remains constant at

$$[0.9] \quad h(t) = \lambda \exp(-\lambda t) / (1 - \exp(-\lambda t)) = \lambda.$$

An example of a constant hazard is the constant radiation risk of people living close to a nuclear power plant. The constant hazard and the expected value ($E(t) = 1/\lambda$), variance ($Var(t) = 1/\lambda^2$), median ($\ln 2/\lambda$), skewness (2) and kurtosis (6) are essential advantages when implementing this distribution function. Therefore, it is commonly used in simulation studies containing variables with assumed time independence. An $Ex(\lambda)$ -distributed random variable (X) can be simulated directly and easily from a random variable with an equal distribution (U)

$$[0.10] \quad X = -\frac{1}{\lambda} \ln U; U \in [0;1].$$

Of course, it is not realistic to assume a constant hazard for most states. In fact, the exponential distribution function is a subtype of the Weibull distribution function, where the hazard changes monotonously over time. A variable ($t; t > 0$) is Weibull-distributed, if $at^b \sim Ex(1)$, so the distribution function can be stated as

$$[0.11] \quad F(t) = 1 - \exp(-at^b),$$

the density function as

$$[0.12] \quad f(t) = abt^{b-1} \exp(-at^b).$$

The survival probability

$$[0.13] \quad s(t) = \Pr(t > t_0) = 1 - F(t) = \exp(-at^b)$$

and the conditional survival probability

[0.14]

$$s(t, t_0) = \Pr(t_0 + \Delta t < t | t > t_0) = \frac{1 - F(t)}{1 - F(t_0)} = \frac{\exp(-\alpha(t_0 + \Delta t)^\beta)}{\exp(-\alpha t_0^\beta)} = \exp(-\alpha((t_0 + \Delta t)^\beta - t_0^\beta))$$

show a direct time dependency. The hazard rate [0.15] $h(t) = \mathbf{a} \mathbf{b} t^{b-1}$ is a function monotonously increasing or decreasing with time, depending on whether $\mathbf{b} > 1$ or $\mathbf{b} < 1$. For $\mathbf{b} = 1$, the Weibull distribution is equivalent to an exponential distribution where $\mathbf{1} \equiv \mathbf{a}$. For $1 < \mathbf{b} < 2$, the hazard function exhibits a concave growth. If $\mathbf{b} > 2$, the hazard accelerates continuously, with $\mathbf{b} = 2$ it acquires the property of a linearly increasing hazard. Combined with a Monte Carlo variable (U), a Weibull-distributed variable is calculated as follows:

$$[0.16] \quad X = \exp\left(\frac{1}{\mathbf{b}} \ln\left(-\frac{1}{\mathbf{a}} \ln U\right)\right).$$

More sophisticated distributions, for example a Weibull-like distribution where $\mathbf{a} = \mathbf{a}(t)$, can exhibit a hump-shaped or u-shaped hazard curve, corresponding to risk sets often observed in micro data. Of course the Weibull-distribution can also depend on other variables than time $\alpha = \alpha(x)$. $\alpha = \alpha(x)$

Regression models for estimating transition probabilities

PROBIT and LOGIT regressions as well as multiplicative hazard models have been developed to estimate the hazard of binomial or multinomial outcomes. When calculating

$$[0.17] \quad h(t) = a + b_1 x_1 + b_2 x_2(t)$$

we are faced with the problem that the right hand side of the equation normally exceeds the [0;1] interval. Some monotone transformation is necessary in order to stay within the limitations of a probability measure. Assuming a logistic distribution of the exogenous variables, the LOGIT transformation simply computes the log of the relation of probability and counter-probability of an event. The LOGIT value for $h(t)$ is defined as

$$[0.18] \quad \ln(h(t)/(1-h(t))) = a + b_1 x_1 + b_2 x_2(t),$$

thus both sides can vary between $(-\infty; \infty)$. In case the hazard rate varies autonomously over time, the LOGIT equation merely has to be expanded to

$$[0.19] \quad \ln(h(t)/(1-h(t))) = a(t) + b_1 x_1 + b_2 x_2(t).$$

Assuming a cumulative normal distribution of the exogenous variables, the PROBIT transformation calculates the standardized cumulative normal distribution

$$[0.20] \quad \Pr_t = F(Z_t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{Z_t} \exp(-t^2/2) dt, \text{ so that}$$

$$[0.21] \quad Z_t = F^{-1}(\Pr_t) = \mathbf{a} + \mathbf{b}_1 x_1 + \mathbf{b}_2 x_2(t).$$

In a multiplicative hazard model, the duration model considers the fact that the calculated random variable is typically an element of a life-cycle process in which several events can

occur. The (log) hazard for switching from state j to state k consists of a ‘baseline’ hazard a , a set of exogenous influences x , the duration in the current state H and unmeasured heterogeneity that may also depend on state spells, age, etc.

$$[0.22] \quad \ln h_{jk}(t) = a_{jk}(t) + b_{jk}x + c_{jk}H + \delta_{jk}z$$

Several regression techniques developed within the field of econometry may also be used in MSMs. OLS and GLS regressions are usually suitable for estimating continuous outcomes. For extrapolation with seasonal decomposition, ARMA and ARIMA methods may be used. 2SLS and 3SLS instrumental variables techniques can be used to take into account hidden exogenous variables.

Cohort-component methods

Besides all methods designed to estimate the survival within a state, cohorts are often predefined by a group of such basic variables (X) as age group, sex, education and social status. A specific state duration (s_{ijklm}) is calculated for every combination of the variables (x_{ijkl}) within an observed state (y_m). Then the derived hazards (h_{ijklm}) are inserted for every agent growing into this cohort (c_{ijkl}) and being within the state (m) in each simulated period. This procedure does not require any assumptions concerning the specific form of the probability distribution. However, some caution is advisable. First of all, the states have to be described rather exactly in order to identify realistic duration probabilities. In the cohort-component approach, even the main cohorts (in this example gender (i), 5-year age groups (j), educational level (k) and social status (l) yield an $i \times j \times k \times l$ -space measuring $2 \times 20 \times 6 \times 5$ or 1200 cells). This involves a large amount of data. Moreover, these cohorts have to be multiplied by all possible states. Some of the created subgroups are very likely to be underrepresented within the data, so these cells are initially left blank. Their hazard has to be interpolated or copied from comparable states of the cohort(s) in the state. With a predefined set of cohort-building variables, a cohort-component approach for calculating the hazards soon loses its straightforwardness. Moreover, a very broad sample is needed to be able to estimate transition probabilities.

Generating cohorts distinguished by a predefined group of variables quickly creates extremely large numbers of cells. Instead, multivariate discriminant analysis procedures identifying significant differences between groups can be established. In this way, almost identical groups that were separated in a common cohort-component procedure can be kept within one cohort. This leads to a sustainable reduction in the number of cells.

Statistical matching

Besides the techniques taken from classical econometry and biometry, additional means have been developed by MSMs. First of all, there is the method of statistical matching. The idea is to find a donor of data within the sample of observation. The characteristics of this

donor should be similar, close to or complementary to a receiving unit. Once a donor has been identified, the required information can be imputed from the donor's dataset to the receiver's.

If only a few data of a variable are missing, they can be supplemented using standardized imputation procedures. However, more sophisticated procedures have to be employed to substitute missing or mostly unfilled variables. In some cases, an instrumental variable can be recreated by computing it with parameters found for regressions in other datasets. As mentioned above, another widely used method is the creation of classified medians of cohorts. It is rather simple to calculate medians or averages of cohorts defined as classes with the same value for such variables as age, gender and family income cohorts, but identifying the best regression is more difficult. Nevertheless, the regression approach is often favored because of its accurateness. Similar to the regression techniques described above, multinomial LOGIT estimators are commonly used to determine imputed values of variables that may have more than two values.

In addition, some variables can be used to match individuals of the simulated population, e.g. identifying partners, raising families, etc. Moreover, observed behaviors of people can be copied to those matched with the observed. Differently to other prediction methods, no further assumptions regarding the underlying distributions of the used variables are needed.

The artificial creation of agents interacting in MSMs contains all steps described above. First, the new agent 'inherits' the main characteristics from a donor's dataset. Then his/her missing variables are imputed by inserting the cohort median or calculating the regressions for imputation. Then the life path and the interactions with existing agents are simulated.

Especially in micro surveys, the most prevalent data problem is that the heterogeneity assumed and observed afterwards does not fully correspond to real heterogeneity. For example, some job search theories imply that the hazard rate for finding a new job decreases with the length of unemployment due to the 'hysteresis-property' of labor markets. This conclusion can be drawn from a macro perspective. However, when studying individual properties and behavior, some additional caution has to be exercised. The macro statement does not consider that individuals with a high hazard rate drop out of the observed sample soon. As time goes by, this selection process yields risk sets that contain individuals with predominantly low risks. For this reason, it is extremely difficult to distinguish a hazard rate decreasing over time from other structural effects. The only way to handle these sources of unobserved heterogeneity is to try to incorporate additional indicators of this heterogeneity into the model. This may require the imputation of additional variables.

When simulating the behavior of agents based on commonly used static cohort discriminants, beliefs, opinions, attitudes and life (segment) concepts may be important sources of unobserved heterogeneity. Introducing discriminant analysis regarding these variables, agents can be assigned to dynamic groups of people with similar goals and attitudes and hence similar behaviors. In the simulation, the discriminant is kept while group membership of people is checked dynamically. This way, it is possible to study additional dynamics that remain hidden if only conventional, state-based discriminants are used.

III. The FAMSIM prototype

FAMSIM –(an acronym for dynamic ‘Family Microsimulation’) was developed within the framework of a feasibility study conducted to elaborate a dynamic microsimulation model permitting projections and the evaluation of family policies. The study was carried out by the Austrian Institute for Family Studies (ÖIF) in collaboration with the International Institute for Applied Systems Analysis IIASA.

FAMSIM is based on female biographies collected in the Family and Fertility Survey (FFS), a standardized survey available for more than 20 countries. The FAMSIM feasibility study included the development of a model prototype mainly covering demographic behavior as well as school and work histories (Lutz 1997, Spielauer 2000).

The idea to produce this family microsimulation model was closely connected with the planning and implementation of the Austrian Family and Fertility Survey (FFS) that was carried out by the Austrian Institute for Family Studies in 1995–1996. (Dobelhammer 1997) What makes this project unique is the fact that the FFS retrospective event history data are available for more than 20 countries in a standardized way. This allows for international comparative studies and substantially extends the applicability and opportunities of the microsimulation project. This fact also proved to be of interest to the European Commission, which decided to cosponsor the development of a prototype model that was finished in 1997.

In 1999, the prototype model was adapted for use in Sweden in collaboration with the Spatial Modeling Center in Kiruna, Sweden, and the FAMSIM software to run the model was developed. In the following year, Belgian, Italian and Spanish FFS data were processed in order to estimate the model parameters for these additional countries. While FFS data enable us to generate individual biographies or event histories in a series of important family-related events, FAMSIM can be viewed as a way to continue (or simulate) all of the biographies that were recorded in the FFS but were truncated in the interview.

The following table gives an overview of all FFS data that are currently available. The typical female sample size is around 4,200. Data differ in the age span of respondents as well as in the year in which the survey was conducted. Meanwhile, a second round of the survey is planned for various countries, and additional countries are expected to join the group of FFS countries.

	Women	Men	Time of interview	Age group
Austria	4500	1500	12/95-5/96	20-54
Belgium	3000	2000	3/91-9/91	20-40
Canada	7500	6000	1/90-3/90	15-54
Estonia	5000	-	1/94-8/94	20-69
Finland	4000	2000	8/98-1/90	22-51
France	3000	2000	3/94-4/94	20-49
Germany	6000	4000	7/92-8/92	20-39
Holland	5100	3800	2/93-3/93	18-42
Hungary	4000	2000	11/92-12/93	18-41
Italy	4800	1200	11/95-2/96	20-49
Latvia	2700	1500	9/95-10/95	18-49
Lithuania	3000	2000	10/94-11/95	18-50
New Zealand	3000	-	10/95-10/95	20-59
Norway	5000	2000	10/88-5-89	20-43
Poland	4500	4000	11/91-12/91	18-49
Slovenia	2800	1800	12/94-12/95	15-45
Spain	4000	2000	8/94-12/94	18-49
Sweden	4200	2300	10/92-5/93	22-44
Switzerland	4200	2000	10/94-5/95	20-49
USA	10500	-	1/95-10/95	15-44

The main purpose of the survey was to collect detailed data concerning the current familial living conditions and the biographies of adults, with a focus on partnerships, births, work experience and education. The FFS was designed to complement existing official statistics. In many countries, it was the first source providing information on biographical interactions between education, work experience, cohabitation, fertility and living arrangements. At the international level, the FFS is coordinated internationally by the Population Activities Unit (PAU) of the Economic Commission for Europe (UN/ECE).

Characteristics of FAMSIM¹

As mentioned above, the FAMSIM prototype contains very limited economic characteristics and no policy variables. Therefore this model mainly serves as demographic module or initial building block of future developments that will incorporate various additional characteristics in order to become an appropriate model for policy evaluations.

¹ For an extensive description of the model please see the feasibility study as published in Lutz (1997).

Some extensions to the model envisaged for the next step of model development are presented in the last chapter of this paper.

- The data basis of the FAMSIM project are the female event histories generated from FFS data. Therefore, the simulated micro units are exclusively women. All other persons in the family along with relevant household characteristics are attached to the female data-records as attributes.
- FAMSIM is a discrete time model with ‘atypically’ small time units (months) to avoid that more than one event happens in one time unit. For a discussion of how to deal with time – continuous vs. discrete and the selection of time units – see Galler (1997).
- The history events that are considered are the beginning and end of different kinds of partnerships, school enrolment, paid work and the beginning of pregnancy followed by births. The model deals with two types of transitions: those with a binary outcome and those with a three-category outcome. The transitions are determined by a logistic expression representing the probability that a variable changes its state in a specific simulation period.
- The life histories generated from the questionnaire start at the women’s 15th birthdays. The characteristics of children younger than 15 are implemented as attributes of the mother. When they turn 15, they enter the simulation as a micro unit in its own right.
- FAMSIM is a ‘self reproducing’ model. The ‘open architecture’ permits the creation of additional (virtual) individuals, e.g. births.

While FFS-data are indispensable for estimating the behavioral equations based on event history data, the starting population can also be generated from other sources (e.g. ECHP data), provided the necessary variables are known. To make the model suitable for policy evaluations, economic characteristics will have to be imputed from other data sources and different data sources will have to be matched.

Variables and transitions

The base of FAMSIM is a logistic regression model of 13 behavioral equations used to estimate the probabilities for the following transitions. A summary of estimation results for five countries can be found in the appendix; for full statistical output see Spielauer (2000).

Transitions with binary outcomes (yes/no):

- beginning of pregnancy followed by birth (transition probabilities for first, second, third and further births are estimated separately)
- beginning of school enrolment
- end of school enrolment

- beginning of paid work
- end of paid work
- end of marriage

Transitions with 3-category outcomes (a/b/none):

- exiting single status: (a) single to cohabitation (b) single to marriage
- exiting cohabitation status: (a) cohabitation to marriage (b) cohabitation to single

The FAMSIM-prototype is based on a set of 12 status variables. All variables are derived from this set. The following table contains a complete list of used variables. (D) indicates dummy variables.

AGE	Age in months / 12
AGESQU	AGE*AGE
COHAB	(D) Living in non-marital cohabitation
TOTCOH	Number of non-married months in current partnership / 12
MARRY	(D) MARRIED
TOTMAR	Number of married months in current partnership / 12
SCHOOL	(D) enrolled in school
TOTSCH	total months of education since 15th birthday / 12
WORK	(D) paid work
TOTWORK	total months working / 12
LTREND	Logarithm of time in months/12 since 1940
BINT1324	(D) 13-24 months after last birth
BINT2536	(D) 25-36 months after last birth
BINT37P	(D) more than 36 months after last birth
PARITY1	(D) one child
PARITY2	(D) two children
PARITY2P	(D) two and more children
PARITY3P	(D) three and more children
PARITY4	(D) four children
PARITY5P	(D) five and more children
PGDUR13	(D) in first three months of pregnancy
PGDUR46	(D) in fourth to sixth month of pregnancy

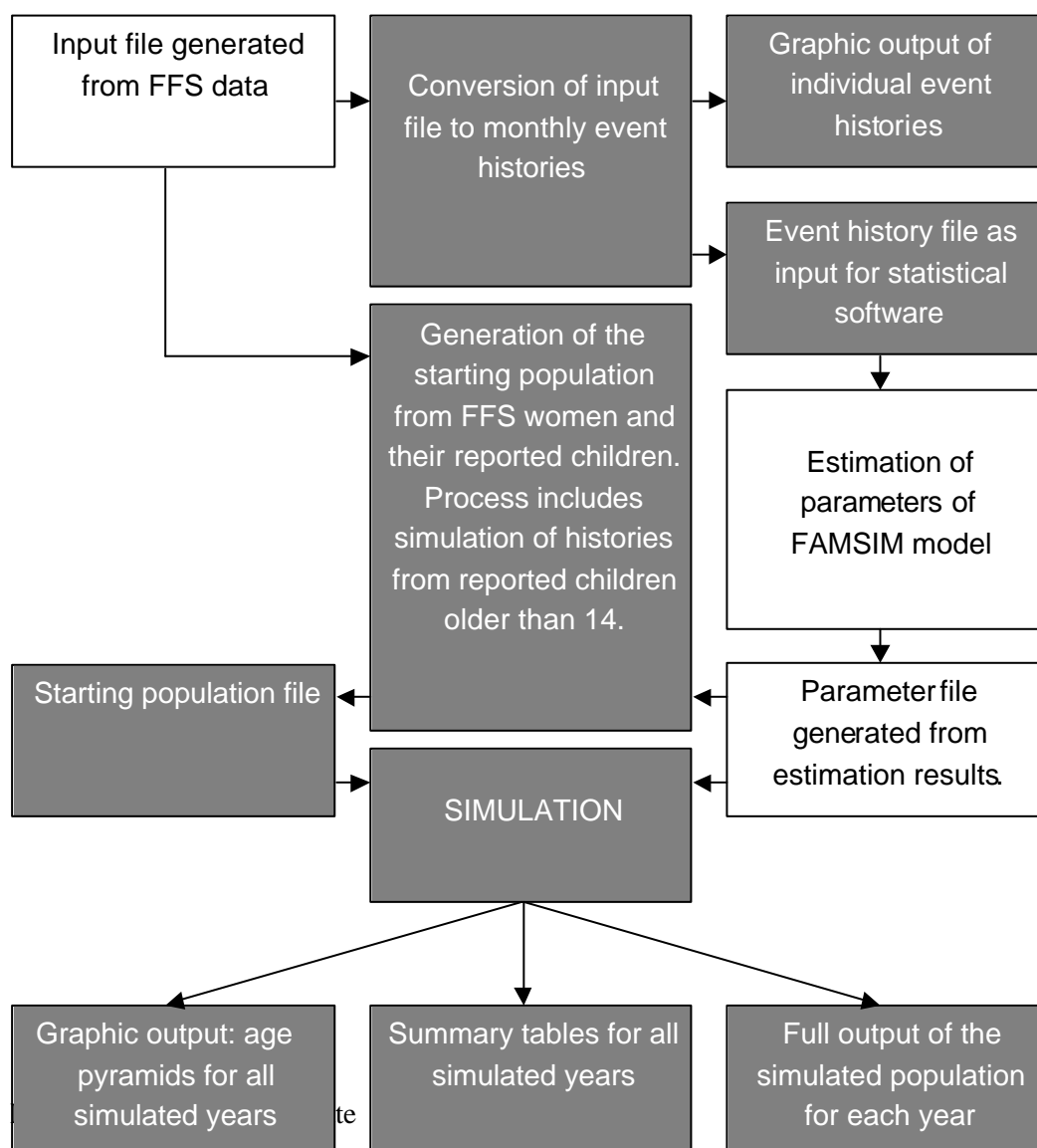
PGDUR79 (D) in seventh to ninth month of pregnancy

The FAMSIM Software

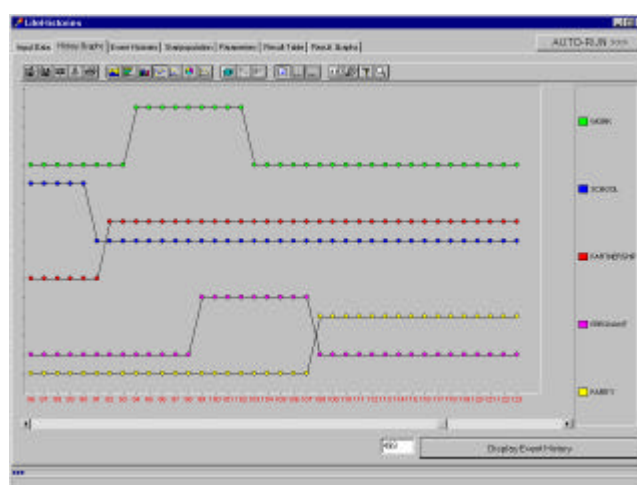
The FAMSIM software was developed as an integrated microsimulation tool supporting all steps of the microsimulation process:

- conversion of FFS survey data to monthly event histories
- generation of the starting population
- execution of microsimulation experiments under various scenarios
- graphic and spreadsheet output of event histories and simulation results

The following diagram summarizes the 'microsimulation procedure' and the features of the microsimulation software (dark boxes).



In order to be able to estimate the behavioral equations, the event histories of all individuals in the sample have to be generated on a monthly basis. For this purpose, the computer software also converts FFS data to the files used for the econometric estimation of the 13 behavioral equations. The output file contains a minimum of 54 variables that cover the FAMSIM prototype model and fully describe all states and transitions. Additionally, variables for time-invariant personal attributes can be added, e.g. the number of siblings. For the typical FFS sample size of around 4,500 women, more than a million of monthly data records are generated. As a byproduct, the event histories of all individuals of the survey can be graphed on a monthly basis and the program allows to 'browse through' these graphs as displayed in the following figure.



Parallel biographies (example) as recorded in the FFS data

The output file(s) generated by the software can be read in by any statistical software package that can estimate logistic regressions. The estimated parameters of the 13 regression equations are then read by the computer program. If needed, they can be manually manipulated before running the simulation.

Starting populations are generated directly from the FFS survey. A number of problems had to be solved, especially regarding weighting. In the Austrian sample, women with children are overrepresented and the age structure is distorted when using one-year age groups. New weights were calculated to make the sample representative regarding parity and age. The automated generation of the starting population is a part of the software package. The children in the starting sample are generated from the information provided by their mothers in the sample. In this respect, two problems had to be solved:

First, as only women between 20 and 54 years were interviewed, no information was available from persons under 20 with mothers older than 54 years. As such people constitute only a small proportion among children and teenagers, the problem was solved by re-weighting. The second problem was also connected with the limited age span of the respondents (starting at the age of 20, while simulation (and detailed life histories) starts at the

age of 15). This problem was solved by simulating the life histories of teenage girls from 15–19, beginning at their 15th birthday until their current age, using the algorithm that was applied to all individuals in the main simulation process.

As an additional feature of the program, a Census-like output can be generated and exported, in the form of an Excel-spreadsheet, for the starting population or any simulated population. This output file can then be imported to statistical packages for more detailed descriptive and other analyses.

The next step is the actual simulation, beginning with the starting population and continuing the individual life histories by Monte Carlo simulation on a monthly basis. For every period and individual, the probability of the different applicable events is calculated from the logistic expressions. The probabilities of transitions with binary outcomes are calculated using the formula:

$$[3.1] \quad p = \frac{e^{B_i x_i}}{1 + e^{B_i x_i}}$$

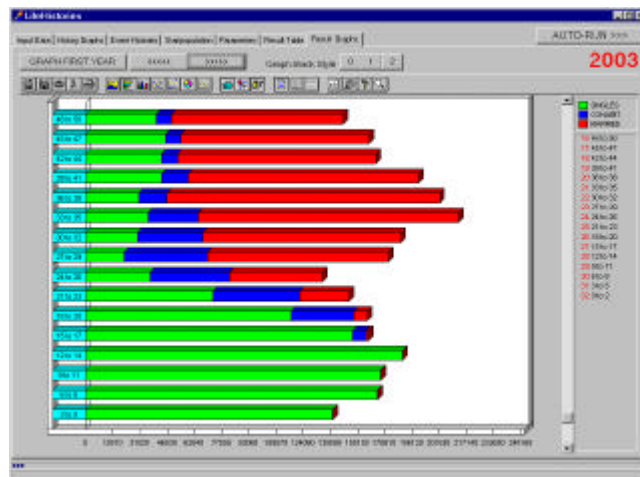
Transitions with three-category outcomes are based on the formula:

$$[3.2] \quad p_1 = \frac{e^{B_{1i} x_i}}{1 + e^{B_{1i} x_i} + e^{B_{2i} x_i}} \quad p_2 = \frac{e^{B_{2i} x_i}}{1 + e^{B_{1i} x_i} + e^{B_{2i} x_i}}$$

B_i represents the estimated logits and x_i stands for the variables used in the equation.

A simulation run typically comprises 50 years, but any other number can be selected in the program. The simulation result is summarized in tables describing the composition of the virtual society in age groups of three years. The output contains the total number of individuals by different living arrangements and by number of children as well as fertility rates and number of births. Tables are produced on a yearly basis showing the simulation result for every simulated year.

Simulation results can be visualized as dynamic age pyramids, depicting such results as the age-specific composition of the simulated society by living arrangement for every simulated year and allowing to ‘browse’ through time. The following figure displays a typical graphic simulation output.



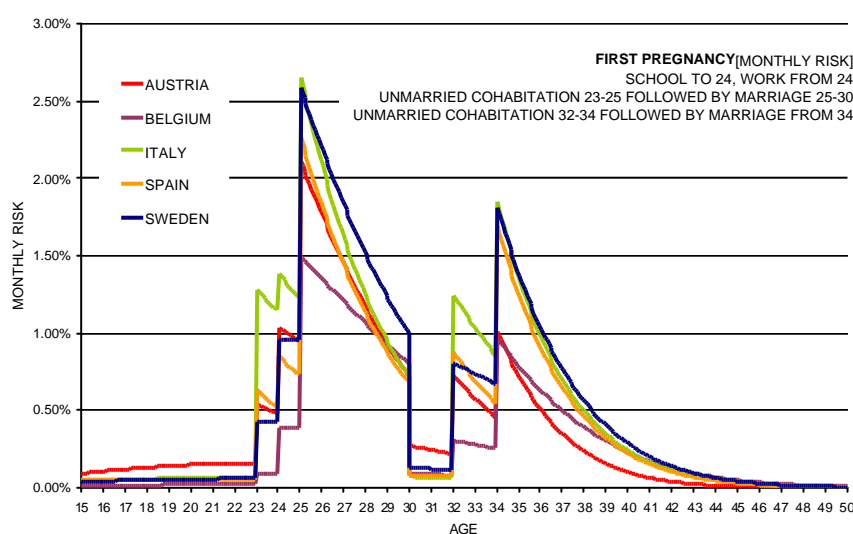
Projected age pyramid by living arrangement: single, unmarried cohabitation, marriage

Estimation results: Examples

This section illustrates the estimation results for some of the 13 logistic regressions. To visualize the results, example life courses are used and the changing risks are calculated for these examples on a monthly basis. These example life courses were selected for demonstrative use only and should not be taken as 'representative life courses'. Risk patterns were calculated for Austria, Belgium, Italy, Spain and Sweden and can be compared in the following graphs.

First pregnancy leading to birth

The following figure shows the monthly risk of a first pregnancy for a woman finishing education and starting to work at age 24, who lives in unmarried cohabitation from age 23 to 25, followed by marriage to her partner. At the age of 30, this marriage is dissolved and the woman remains single for two years. Then she once more lives in unmarried cohabitation until she marries for the second time at the age of 34.

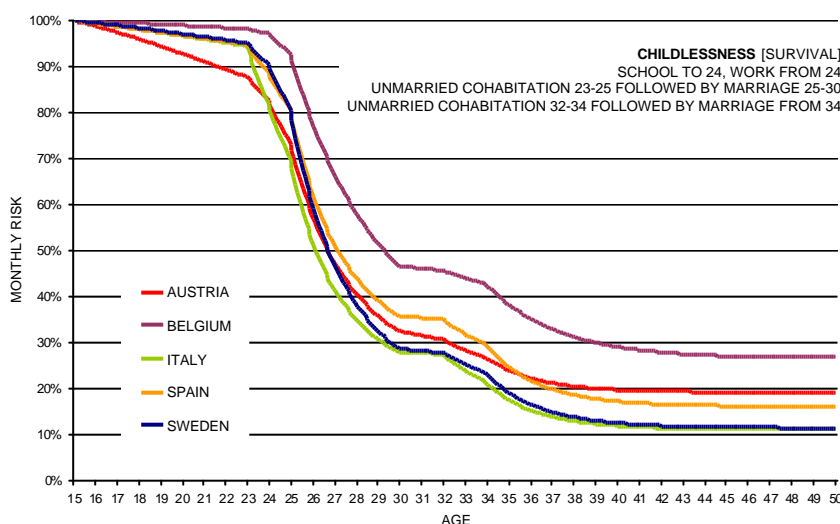


Risk of first pregnancy for an example life course

Risk patterns differ significantly for the 5 countries, with Italy showing the highest risk in phases of unmarried cohabitation, while marriage and having children “goes together” to a much higher extent in both Sweden and Italy. It should be noted that marriage is highly ‘selective’ in Sweden where 50% of the children are born out of wedlock, while unmarried cohabitation is still a rather uncommon living arrangement in Italy, with fertility patterns much closer to that of married couples than in other countries. Comparing the first and second

marriage, the pregnancy risk remains high in Sweden, Italy and Spain, being about 75% higher than in Austria and Belgium. In contrast, the pregnancy risk in phases of not living together with a partner is almost three times higher in Austria than in the other countries.

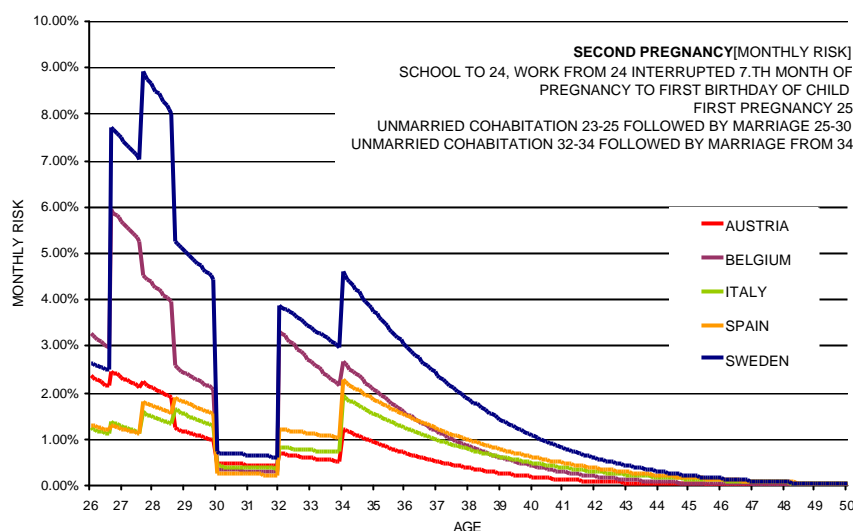
For this life course, probabilities of staying childless differ considerably between the five countries, with Sweden and Italy having the lowest risk (about 11%), followed by Spain (almost 17%) and Austria (slightly below 20%). In Belgium, there is risk of around 28% that a woman remains childless. In all likelihood, this figure is the result of projecting a short time trend in a rather unrealistic way. Note that the survival curves for remaining childless are calculated for women currently aged 15, based on the assumption of fertility trends as estimated from the data.



Survival of staying childless for an example life course

Second pregnancy leading to birth

The following figure shows the monthly risk of a second pregnancy for a woman finishing education and starting to work at age 24, who lives in unmarried cohabitation from age 23 to 25, followed by marriage to her partner and getting pregnant for the first time at age 25. At the age of 30, this marriage is dissolved and the woman remains single for two years. Then she once more lives in unmarried cohabitation until she marries for the second time at the age of 34.



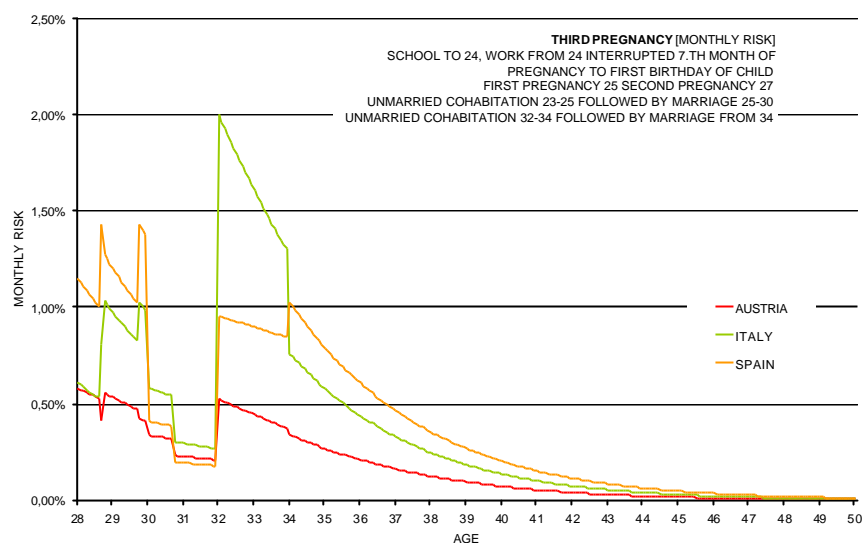
Risk of second pregnancy for an example life course

Regarding second pregnancy, differences between the countries are more evident than for first pregnancies. Monthly risks are up to 5 times higher in Sweden than in other countries. Although marriage is highly ‘selective’ in Sweden and tends to be a living arrangement usually associated with having or planning more than one child, this result is quite unrealistic. In fact, it shows one of the main weaknesses of the model, namely the inclusion of (the logarithm of) calendar time as explanatory variable. In the years before the Swedish FFS survey was conducted – 1992 – Sweden experienced a significant change in the timing of second and following births due to policy changes (Kohler 1999). This is interpreted as a quantum effect in the model, and the trend is continued over time, leading to this biased result in the reference year (2000) of the calculation. Data-related problems might also explain the Belgian pattern, in particular as the estimation of the model for Belgium is based on data that are four years older than the ones used in the remaining countries.

The probability of having a second child in the second marriage is lowest in Austria, while risk levels generally double for Austria, Spain and Italy when the woman gets married the second time, as compared to the preceding unmarried cohabitation.

Third pregnancy leading to birth

The following figure shows the monthly risk for a third pregnancy for a woman finishing education and starting to work at age 24, who lives in unmarried cohabitation from age 23 to 25, followed by marriage to her partner and getting pregnant for the first time at age 25, and for the second time at age 27. At the age of 30, this marriage is dissolved; the woman remains single for two years. Then she once more lives in unmarried cohabitation until she marries for the second time at the age of 34.

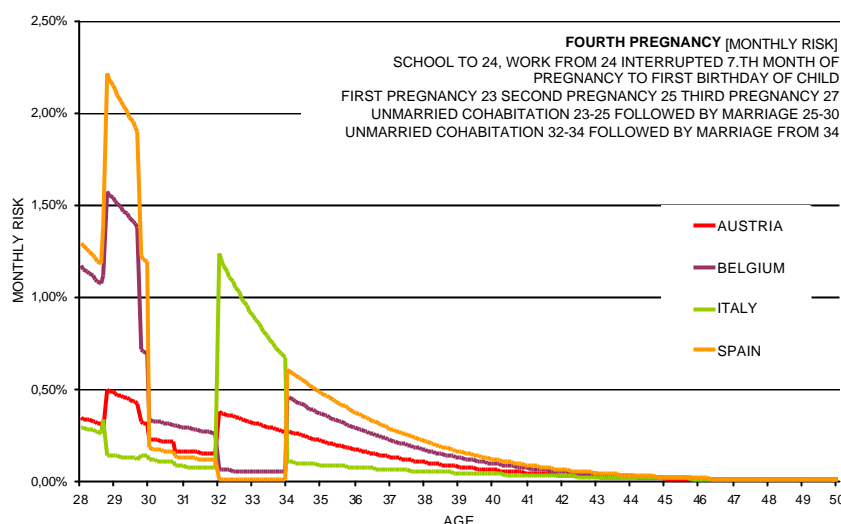


Risk of third pregnancy for an example life course

Pregnancy risks are only displayed for Austria, Italy and Spain, as the results for Belgium and Sweden are unrealistic for the reasons mentioned above. Interestingly enough, the second marriage after two years of cohabitation has no impact on fertility levels regarding third births in Austria, and only a rather small positive effect in Spain, which is leveled out by a faster decrease of risk after marriage. This pattern can also be found with fourth pregnancies under similar circumstances, as can be seen below.

Fourth and further pregnancies leading to birth

The following figure shows the monthly risk for a fourth and further pregnancies for a woman finishing education and starting to work at age 24, who lives in unmarried cohabitation from age 23 to 25, followed by the marriage to her partner at age 25. She conceives her first child at age 23, the second at age 25 and the third at age 27. At the age of 30, this marriage is dissolved, and the woman remains single for two years. Then lives in unmarried cohabitation until her second marriage at age 34.

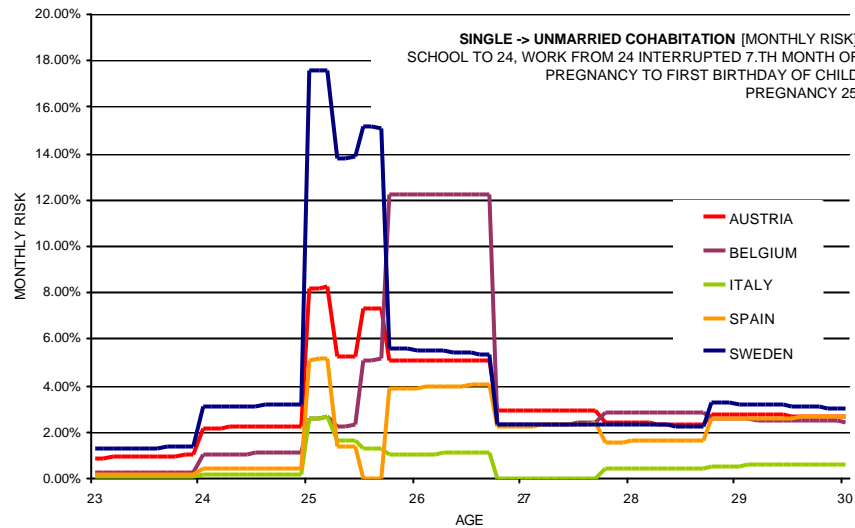


Risk of fourth and further pregnancies for an example life course

Also in this case, monthly pregnancy risks are highest in Italy when the woman starts to live in cohabitation with the second partner two years after divorce, and drop considerably after her second marriage. In contrast, second marriage after cohabitation has no effect on pregnancy risks in Austria, and positive effects in all other countries. Regarding the remaining two years of the first marriage, the curves indicate very high parity progression rates for fourth (and further) births in Spain and Belgium, with rates comparable to first pregnancies in Spain, while the rate is lowest in Italy, the second Mediterranean country included in study.

Partnership formation

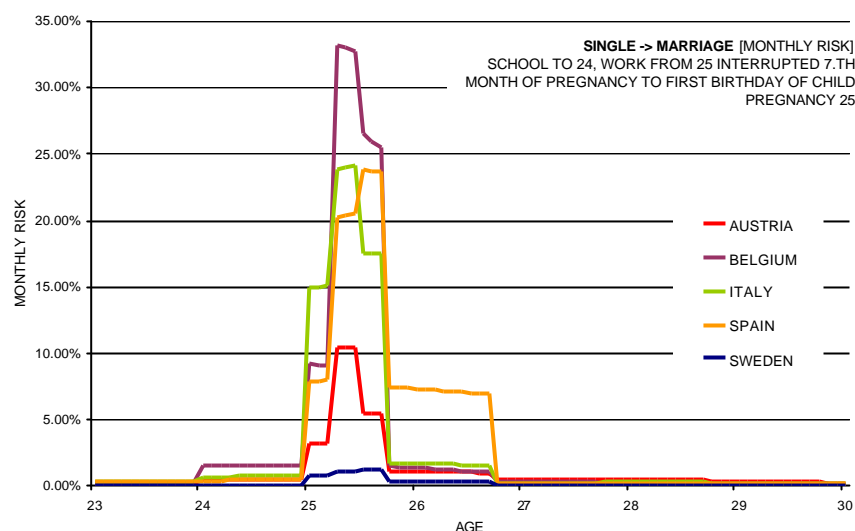
The following figure shows the monthly transition rates from being a single to unmarried cohabitation for a woman finishing school and starting to work at age 24, who gets pregnant at age 25. The working career is assumed to be interrupted from the 7th month of pregnancy until the first birthday of the child. Note that this risk pattern cannot be interpreted independently from marriage risks, as pregnancy plays a very different role as “a reason for getting married” in the different countries.



Risk for transition from being a single to unmarried cohabitation for an example life course

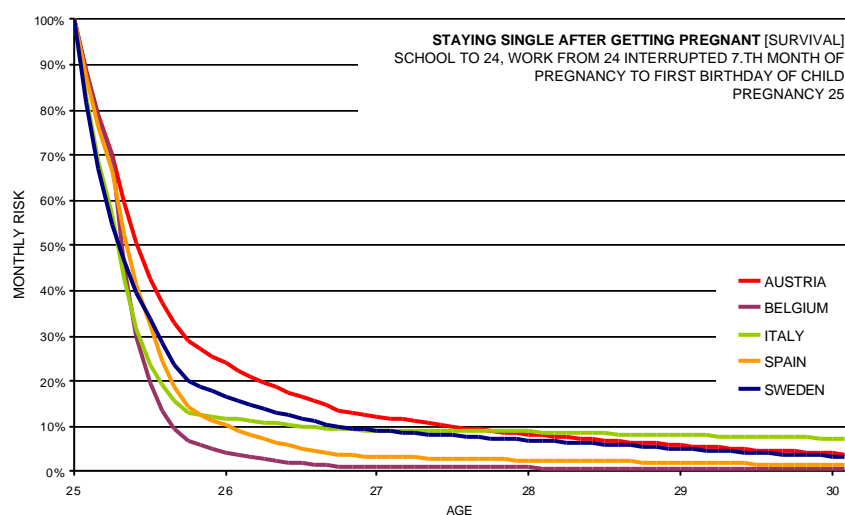
As unmarried cohabitation generally plays a much more dominant role in Sweden as compared to the other countries, monthly probabilities to move into unmarried cohabitation are highest there for almost the entire age interval under observation. Not surprisingly, pregnancy also increases the probability to start an unmarried cohabitation to its highest level in Sweden. Partners move together already in the first months of pregnancy in all countries except in Belgium, where the birth of the child seems to be the event that matters most.

The following figure of the monthly risks of marriage shows the complementary picture. The probabilities of marriage are lowest in Sweden, and only rise very slightly during and after pregnancy as compared to other countries.



Risk for transition from being single to marriage for an example life course

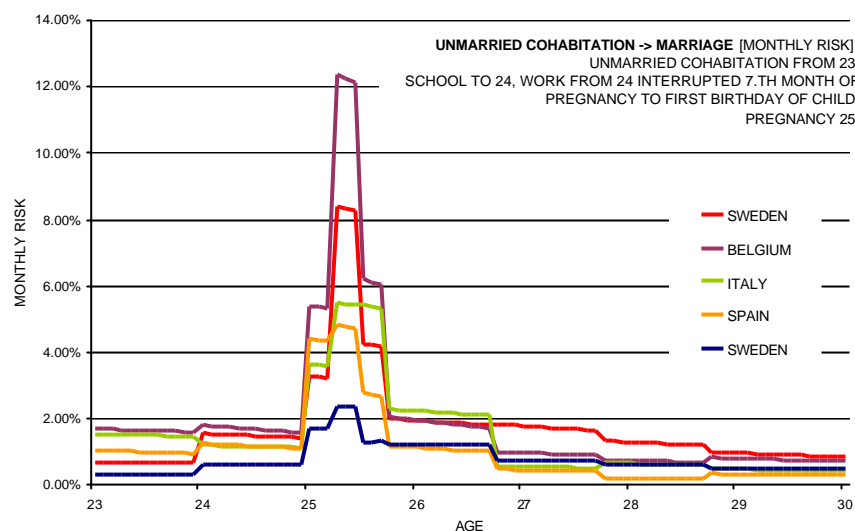
At the time the child is born, the probability of staying single is highest in Austria (around 30%), followed by Sweden (20%) and other countries (less than 15%). Interestingly enough, the survival curve of ‘staying single’ remains relatively flat for single Italian women who have giving birth to a child. Compared to other countries, lone mothers have a much lower probability of new partnerships in Italy.



Survival curve: remaining single after pregnancy for an example life course

The following figure depicts the monthly risk of marriage for a woman living in unmarried cohabitation. Again, pregnancy increases the probability of marriage in varying degrees in the

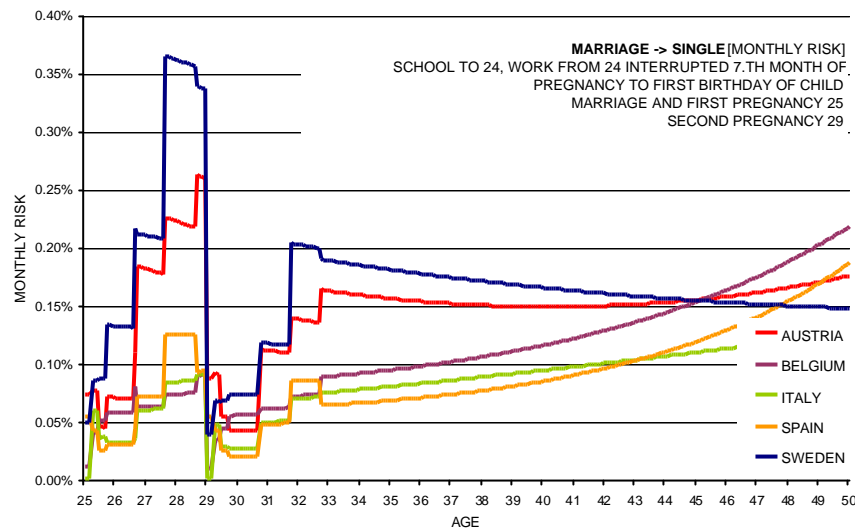
different countries; the highest probabilities are found in Belgium and Austria, and the lowest in Sweden.



Risk for transition from cohabitation to marriage for an example life course

Dissolution of partnership

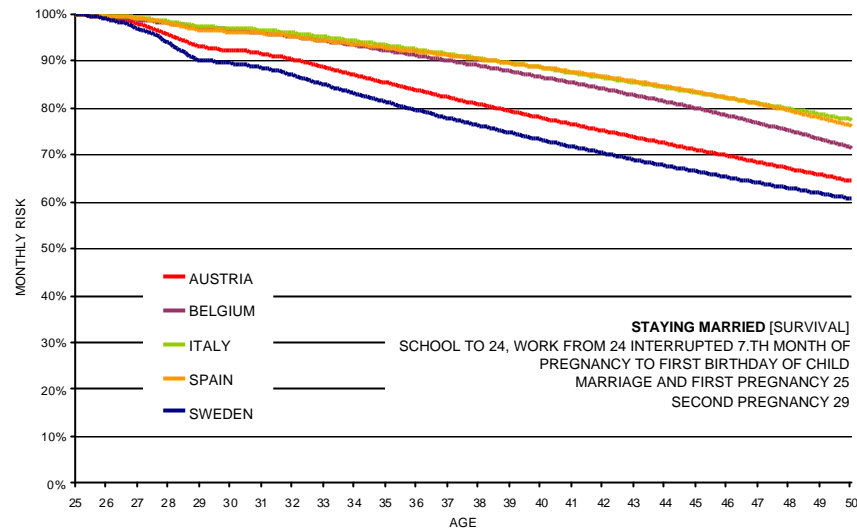
The following figure shows the risk of a divorce for a woman finishing school and starting to work at age 24, who gets married at age 25, and pregnant at age 25 and 29.



Risk for transition from marriage to being single for an example life course

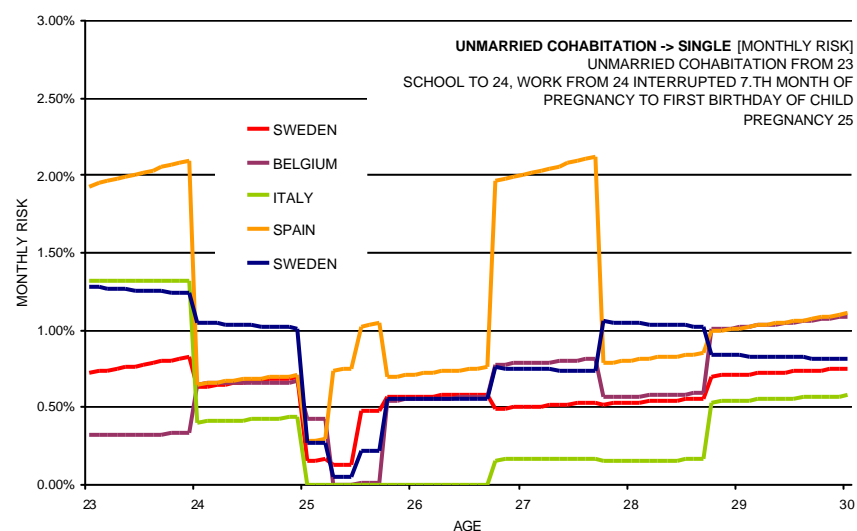
As was to be expected, the risk of marriage dissolution is smallest during pregnancies and peaks two years after giving birth. While monthly risks decrease after that peak in Sweden and stay relatively flat in Austria, they once more increase in the other three countries.

The risk of divorce is highest in Sweden and Austria. The following survival curve shows that, at age 50, the probability of marriage dissolution is about 40% in Sweden, followed by Austria. The lowest probabilities are found in Italy and Spain, where the values are only slightly higher than half of this rate. The second pregnancy at age 29 makes the curves considerably flatter – or marriage dissolution unlikelier – an effect that is especially visible in Sweden and Austria.



Survival curve: staying married for an example life course

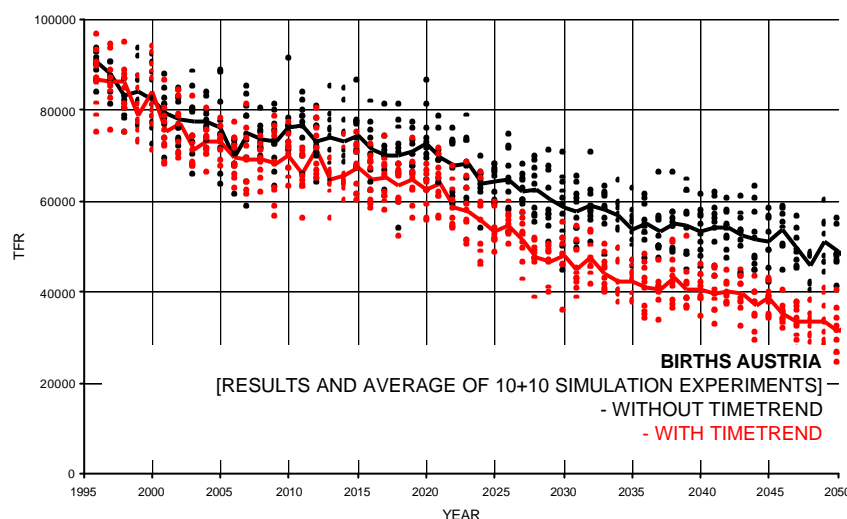
Compared to the risk of divorce, the risk of returning from unmarried cohabitation to single status is around 10 times higher. Unmarried cohabitation is most unstable in Spain, not only due to the high risk of partnership dissolution, but also to the low probability that this cohabitation is followed by marriage.



Risk for transition from unmarried cohabitation to single status for an example life course

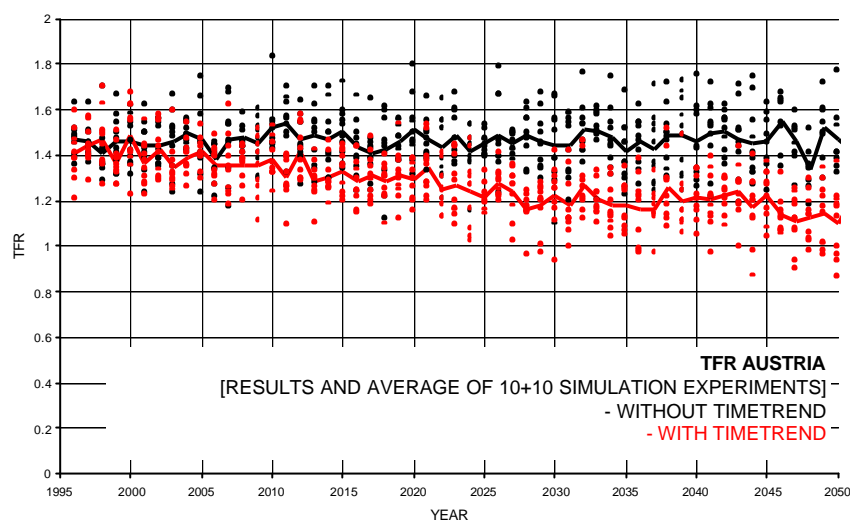
Simulation Results

This section presents simulation results for Austria, Belgium, Italy, Spain and Sweden. The FAMSIM prototype model includes a time-trend variable in the form of the logarithm of calendar time. For this reason, the base scenario assumes that this trend continues into the future. An alternative scenario was simulated for Austria, keeping time constant from the start of the simulation in 1995. The following two figures show projections of births and total fertility rate (TFR) for Austria as a result of ten simulation experiments for each scenario.



Projected number of births in Austria

Continuing the time trend substantially reduces the projected births for the next 50 years. Halting the time trend stabilizes the total fertility rate at the current level, while its continuation would further decrease the TFR from about 1.4 to 1.2 in the next 25 years.

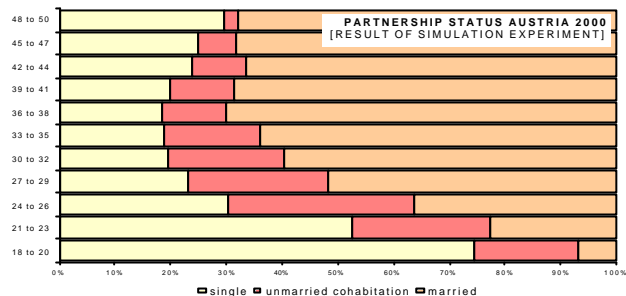


Projected TFR for Austria

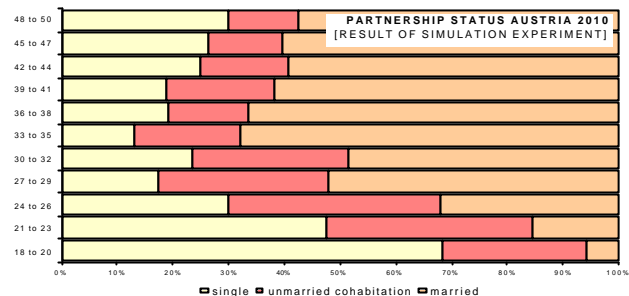
The following pages display simulation results concerning living arrangements and parities for Austria, Belgium, Italy, Sweden and Spain.

Simulation results for partnership forms: 2000 and 2010

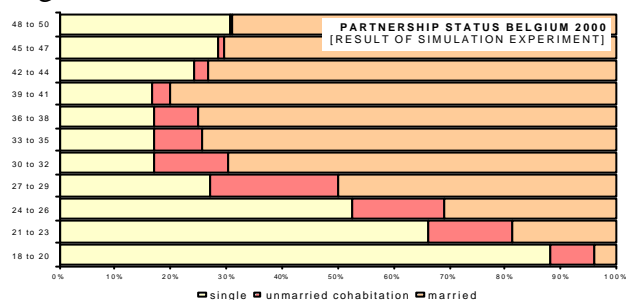
Austria



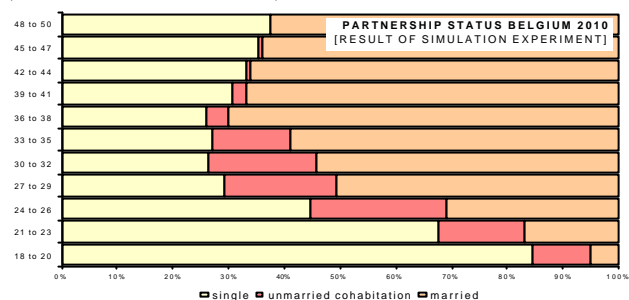
(simulation starts 1995)



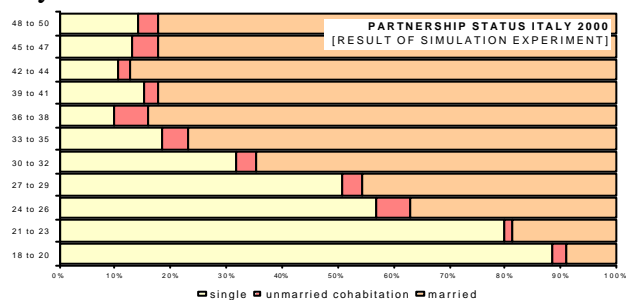
Belgium



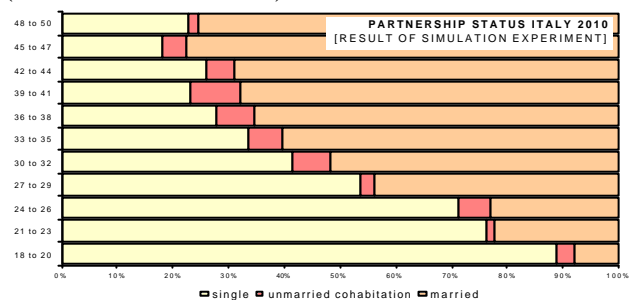
(simulation starts 1991)



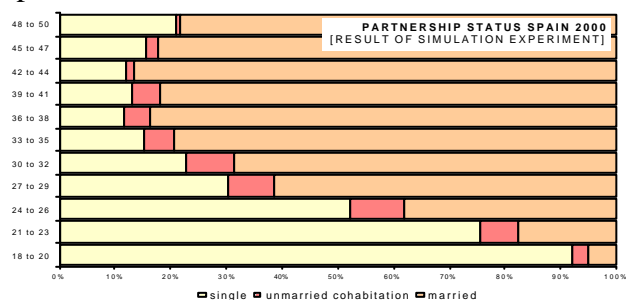
Italy



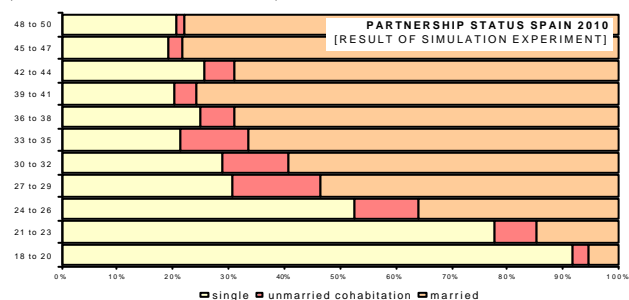
(simulation starts 1995)



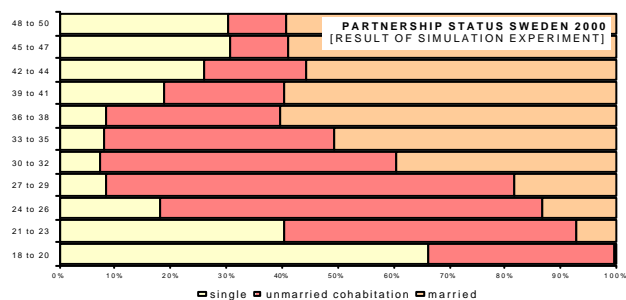
Spain



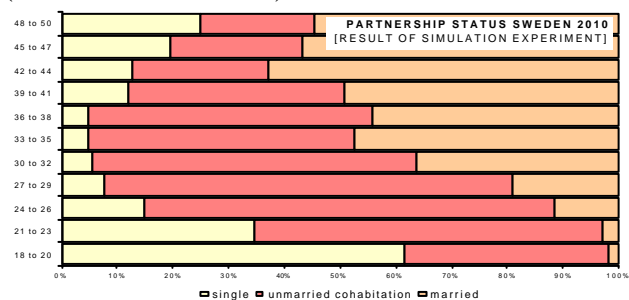
(simulation starts 1994)



Sweden



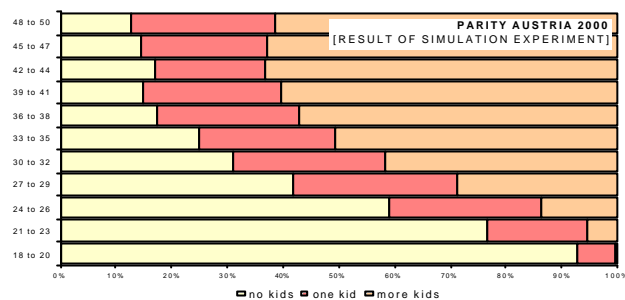
(simulation starts 1992)



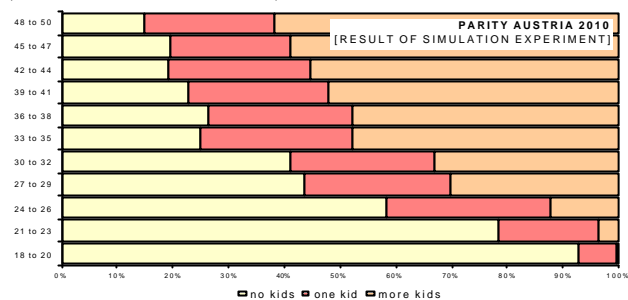
single – unmarried cohabitation – married

Simulation results for number of children: 2000 and 2010

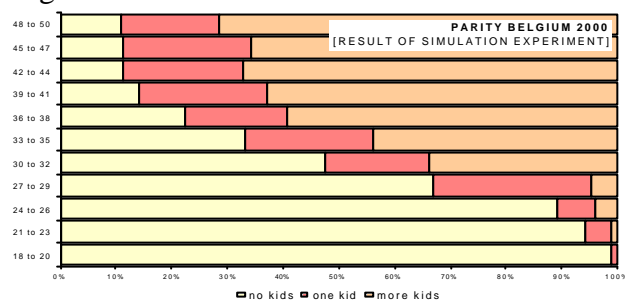
Austria



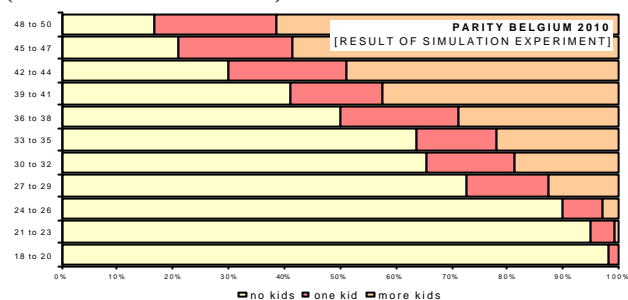
(simulation starts 1995)



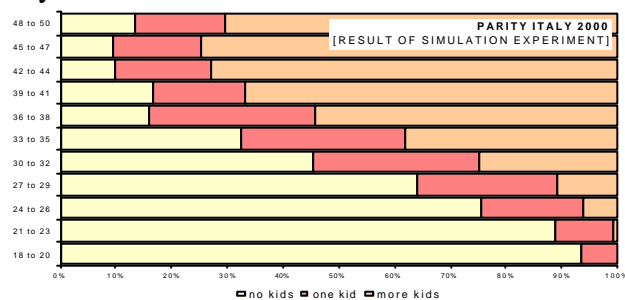
Belgium



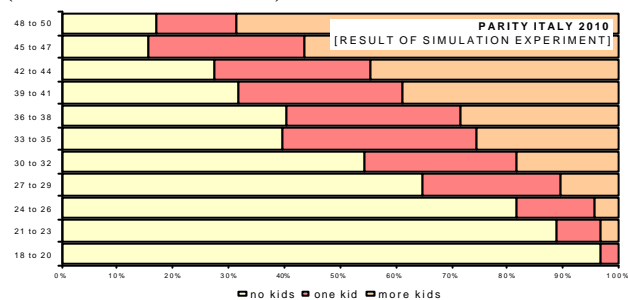
(simulation starts 1991)



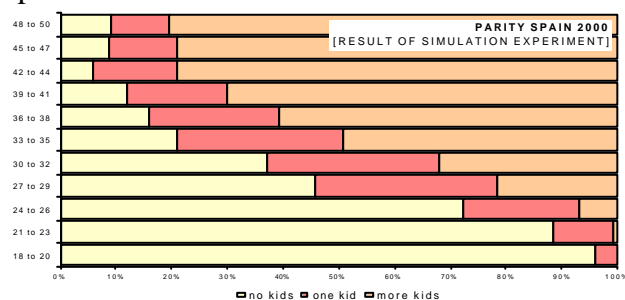
Italy



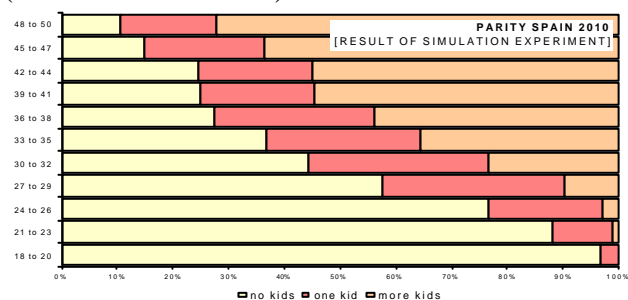
(simulation starts 1995)



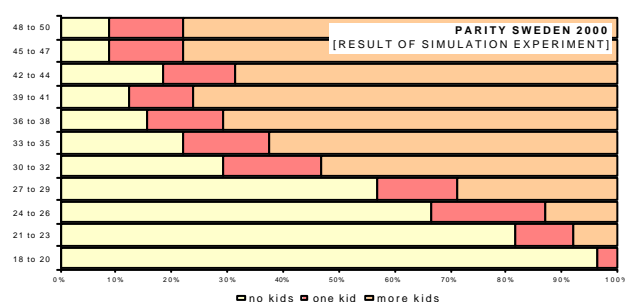
Spain



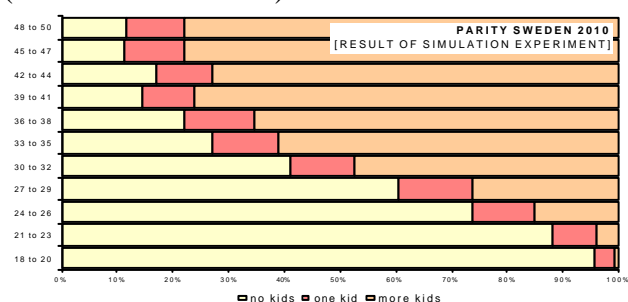
(simulation starts 1994)



Sweden



(simulation starts 1992)



no children – one child – more children

IV. Outlook: the FAMSIM+ project

The focus of the FAMSIM+ dynamic microsimulation project is on family policy evaluation regarding costs, benefits and distribution effects as well as the implications on human capital formation and labor supply. It is based on the FAMSIM feasibility study that included the development of a model prototype for demographic behavior, and introduces economic and behavioral features. This allows us to assess costs of alternative family-related tax and benefit schemes as well as distribution aspects, i.e. to identify the winners and losers of policy changes. Differently to static approaches, dynamic microsimulation allows us to study dynamics over time (e.g. the development of costs or the number of people who receive benefits) and to model behavioral response. As in the original FAMSIM model, the main data source are the event history data collected in the Family and Fertility Survey (FFS) that is available for various countries. These will be matched with other data sources, mainly with the purpose of introducing economic characteristics not contained in FFS data. In the course of this research, a ‘FAMSIM+’ software has been developed both as a flexible and powerful projection and forecasting tool and for the testing different behavioral theories.

Several improvements and extensions are planned in order to further raise the quality and to extend the area of potential applications. Improvements will mainly focus on the modeling of education; major extensions will relate to the explicit inclusion of men who were originally only treated as attributes of the female micro population. This raises many questions in connection with information from various additional data sources. They must be solved in order to include economic characteristics in the model.

Education

A more adequate modeling of education should include information on the institutional characteristics of the school system and school types. If this information is combined with existing numbers and projections on enrollment rates, this could substantially improve the overall accuracy and prediction power of the model. Research regarding population projections has identified education as the single most important variable besides age and sex in determining fertility and mortality (Lutz 1999). Regarding the timing of life events, household formation, marriage and parenting careers are usually started after leaving school, while education is a key determinant of human capital and therefore of income and job careers in economic modeling.

Fertility

Given the fact that no economic characteristics that determine fertility by parity enter the behavioral equations, estimates of future fertility rates have proven quite reasonable in the original FAMSIM model. In order to allow for the modeling of policy effects on fertility,

various improvements can be made, especially regarding the issues of timing and spacing of births. The study of fertility patterns is one of the key applications where microsimulation can be used not only for predictions but also to test theories. Timing and variance effects can bias such period measures as the TFR, making it difficult to directly assess policy effects or changes in cohort fertility. Improved behavioral modeling of fertility, based on event history analysis, can address strategic adaptation to changes in policy and environmental contexts and potentially shed light on and create new insights into these topics.

Migration

Besides fertility and mortality, migration is the third key variable in all population projections. As migration changes the size and characteristics of the population, adding this aspect to FAMSIM is of great importance for policy evaluation. Immigration and emigration are usually included by assuming different scenarios regarding size and characteristics of people leaving and (re)entering the population.

Regarding immigration, a widely used approach, also used in SVERIGE, is (1) to define groups of immigrants based on existing studies, in order to group people according to ‘cultural difference’ and (2) to create external scenarios of immigration flows by groups. This is usually done by cloning existing households of the same group in the base population. Cloned variables include age, sex and earnings while such other features as spatial characteristics might come from external information organized in ‘lookup tables’. This method has proved feasible and easy to handle for most applications.

Another way of generating ‘new immigrants’ is to create a synthetic population of immigrants based on characteristics that depend on scenarios. This permits a more detailed analysis, as policies influencing not only the number but also the types of immigration can be taken into account. This way of modeling may add a lot of flexibility, but would still allow the use of the cloning approach (in this case, the synthetic population would consist of the foreigners of the micro population). Another advantage of this approach is that it allows extending the model to the multi-regional level, which permits the migration between regions (in this case, another micro-population representing another region is used instead of a synthetic population).

Conceptually, emigration is easier to handle, as no new micro-units have to be created, but it only has to be determined, which units leave the population. In a world of increasing migration flows, especially in the context of the European Union, it might be advantageous to keep the units in the population (without counting) in order to allow the modeling of those coming back. Regarding the assessment of family policies, emigration is not a major priority at the moment, but might gain importance in the longer run.

Partnership formation and dissolution

The explicit inclusion of men, who were originally treated as attributes of the female micro –population, implies the necessity of matching partners. Characteristics typically used in matching algorithms are income, age, education level as well as spatial and cultural characteristics. Modeling the matching process is a key task. It entails that the proper characteristics are attributed to the parents, which subsequently affect the behavior of the children. It is also of key importance for tax-benefit analysis to attain a reasonable household income distribution. However, to reduce computer processing, a simple search algorithm is required. Such an algorithm was evaluated and tested in SVERIGE. In FAMSIM, partnership forms are treated as attributes of women and no other information besides a beginning and dissolution of married and unmarried cohabitation are processed. The ability to explicitly match partners is highly dependent on the way in which men are introduced into the model.

In the matching algorithm, speed is an important issue. Even in a female-dominated model, the number of permutations required increases exponentially when searching through the whole male bachelor population for every woman. This considerably slows down the model. In a smart search algorithm, the population of potential bachelors is decreased as much as possible. For example, a woman aged 18 will only look for partners in the age group 20–25. Another way of reducing the search process is to construct a stochastic search model. Here, the number of possible search sequences is determined individually: where some agents obtain several matches, other individuals don't. Combined with other data sources, this matching process is also used to create the starting population for the microsimulation.

Income and labor market participation

Modeling labor-market participation and income flows is a great challenge in MS. Labor-market economics is one of the most widespread and controversial fields in economic theory. Most approaches are based on the neoclassical model. In this model, the labor supply of households is primarily determined by the individual's marginal utility of income and leisure, while the labor demand of firms is generated by the marginal productivity of labor. Labor markets are completely and instantaneously cleared by the unrestricted allocation mechanism of wages. Once labor supply exceeds labor demand, wages simply decline until they reach the (lower) marginal product of the increased labor input and vice versa (it is assumed that other factors remain constant, at least for short periods). If people remain unemployed, they are considered to do so voluntarily. For these people, the marginal utility of income apparently exceeds the market wage. Of course, many underlying assumptions of this base model never materialize in reality. All agents can never be fully informed about the status of the labor market, wages do not adjust freely, employers cannot hire and fire their employees without any legal restriction, agents are not homogeneous, etc. However, these rather unrealistic

assumptions were used in models, and each gave rise to at least one labor-market theory that tried to substitute it with more complex but also more realistic extensions. Search theories have been developed to handle incomplete information; contract theories tried to impose legal and factual restrictions on variations of employment; human capital theory modeled heterogeneous agents at least regarding education and on-the-job-training; efficiency wage theories gave insight into the fact that some labor markets never reach an equilibrium, because employers have rational reasons for paying more than just the market clearing wages to fewer employees; and insider-outsider theories modeled the strategic situation of employees, job entrants and outsiders vis-à-vis the employers. Besides extensions of the neoclassical base model, such other approaches as segmentation models, (post-)keynesian perspectives or disequilibrium models have been developed.

The central task of this MS project is to model the intra-household division of (paid and unpaid) labor over the lifecycle of individuals, taking into account macro developments. Like every econometric study, MSMs also depend on the underlying labor market theory chosen, but within microsimulation, additional parts of a model can be activated for one run, and left deactivated for other research agendas. It is also conceivable to implement different—and in some respects contradictory—(base) models in order to increase the analytical flexibility of the MSMs.

Income developments are always closely related to actually effective labor supply. Besides labor-market participation and wage variations, capital income, private and public, monetary and in-kind transfers also have to be considered. In addition, the aggregated family income has to be harmonized regarding the household structure and differences in regional purchasing power.

Consumption and savings

Depending on the savings rate of the individual household, the streams of income are accumulated to wealth. As different households pursue different saving motives, the individual saving rate can be modeled as an individual function with weight on intertemporal risk aversion (precautionary motive), altruistic intergenerational behavior (bequest motive), and/or the intention to carry out business projects (enterprise motive) or to improve one's personal independence (independence motive) etc. Based on the distribution of saving motives, sets of these competing and/or complementing motives will be assumed for every household in FAMSIM+. In addition, the saving behavior will be influenced by the institutional framework of the social security systems.

As a counterpart of the saving behavior, the household consumption will be calculated. Due to individual preferences of time allocation, the labor market participation also depends, on the household's wealth.

Family policies

Besides immediate costs and benefits, feedback reactions on policies and the long-term distributional and budgetary effects are the most important and interesting questions for policy-makers. They have to weigh present benefits and costs against future benefits and costs. Such decisions encompass many political subjects and influence future labor supply, income, career possibilities, and poverty risks, and might also have an impact on the timing of births and fertility rates.

So far, most of these evaluations of family policies have been based on a static view. This simply means that the paid contributions or taxes are compared to the received allowances, transfers and benefits in kind, at a certain point in time, whereas changes over the time cannot be evaluated. Such static studies can only reveal one dimension of the distributional effects, i.e. their consequences for social groups and income classes. However, long-term effects such as distributions over the whole lifecycle cannot be evaluated with such a technique. To get some insight into distributional effects over the life course, a widely used technique is to generate sample life courses. Individual contribution and payout histories are then calculated and compared for these sample life courses. Problems arise, as these sample life paths are barely representative and do not add up to the true population. As already stated in previous chapters, there is no true alternative to microsimulation for addressing this kind of policy questions.

With FAMSIM+ it will be possible to simulate family-related policies and to trace the distributional effects from the point of introduction to any future point in time. As a consequence, the intertemporal distribution effects among income classes or social groups can be shown. In addition, the intertemporal distributional effects can be analyzed in a broader context, i.e. by including opportunity costs and human capital aspects.

While FFS data will remain the primary data source, the introduction of economic and family policy variables requires the inclusion of a variety of additional data sources, both micro and macro data. Regarding macro time-series policy data, the family-policy database developed by the Mannheimer Zentrum für Europäische Sozialforschung (MZES) will be a valuable source. This database was developed in the framework of the international research project *Family Change and Family Policies in the Western World* and will be run and updated by the Austrian Institute for Family Studies (ÖIF). It covers (1) cash benefits for families in general, (2) cash benefits specially granted to lone parents, (3) monetary transfers guaranteeing a subsistence minimum, and (4) child-care services.

The FAMSIM+ project differs from other microsimulation models in various aspects: First of all, it focuses on family policies and family-related questions. Secondly, it is based on event-history data, and thirdly it has an international dimension that permits international comparative studies.

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Appendix I – Logits

The base of FAMSIM is a logistic regression model of 13 behavioral equations used to estimate the probabilities for the following transitions:

FIRST	first pregnancy followed by birth
SECOND	second pregnancy followed by birth
THIRD	third pregnancy followed by birth
FOURTH+	fourth and further pregnancies followed by birth
SINCO	single -> unmarried cohabitation
SINMAR	single -> married
COSIN	unmarried cohabitation -> single
COMAR	unmarried cohabitation -> married
MARSIN	married -> single
SSCH**	beginning of school enrolment
ESCH	end of school enrolment
SWORK	beginning of paid work
EWORK	end of paid work

A summary of estimation results – the logits of the 13 equations – for Austria, Belgium, Italy, Sweden and Spain – is contained in the following tables; for full statistical output see Spielauer (2000). The first table briefly describes the variables.

** The school history is not recorded in detail in Belgian and Italian FFS data. In the simulation it is assumed, that all individuals are enrolled in school at age 15 and it is only evaluated, if school enrolment ends in a given period.

VARIABLES

INTERCEPT	intercept
PARITY1	one child (dummy)
PARITY2	two children (dummy)
PARITY2P	two and more children (dummy)
PARITY3P	three and more children (dummy)
PARITY4	four children
PARITY5P	five and more children
AGE	age in months / 12
AGESQU	age * age
BINT1324	13-24 months after last birth (dummy)
BINT2536	23-36 months after last birth (dummy)
BINT37P	37 and more months after last birth (dummy)
COHAB	living in cohabitation (dummy)
MARRY	married (dummy)
TOTCOHAB	number of non-married months in current partnership / 12
TOTMARRY	number of married months in current partnership / 12
SCHOOL	enroled in school (dummy)
TOTSCHOOL	total months of school education since 15th birthday / 12
WORK	paid work (dummy)
TOTWORK	total months working / 12
LTREND	logarithm of time in months / 12 since 1940
PGDUR13	in first three months of pregnancy (dummy)
PGDUR46	in fourth to sixth month of pregnancy (dummy)
PGDUR79	in seventh to 9th month of pregnancy (dummy)
PGDUR49	in fourth to 9th month of pregnancy (dummy)

AUSTRIA	FIRST	SECOND	THIRD	FOURTH+	SINCO	SINMAR	COSIN	COMAR	MARSIN	SSCH	ESCH	SWORK	EWORk
INTERCEPT	-8,6391	-8,7587	-6,2426	-5,3352	-13,3516	-10,0826	-9,2394	-1,0846	-8,0033	13,0002	-12,2074	-0,7039	-5,9573
PARITY1					0,9129	0,7290	-0,6355	0,4812	-0,5722		0,3072	-2,1997	1,6449
PARITY2									-0,9376	-0,0017	0,4399	-2,3467	1,4517
PARITY2P					0,5732	0,1822	-0,3126	0,3693					
PARITY3P									-0,9247		-0,3946	-1,9446	1,1070
PARITY4				0,3934									
PARITY5P				0,4217									
AGE	0,4015	0,3525	0,2654	0,2718	0,2999	0,7244	0,2130	0,1364	-0,1729	-1,3815	0,8704	-0,0966	-0,0810
AGESQU	-0,0088	-0,0075	-0,0052	-0,0052	-0,0063	-0,0150	-0,0055	-0,0024	0,0019	0,0172	-0,0178	-0,0014	0,0009
BINT1324		0,4681	0,4120	0,5037	-0,6286	-0,4585	0,1777	-0,0321	0,4596	-1,2786	0,0240	0,8095	-1,8430
BINT2536		0,5269	0,3150	0,2462	-0,8431	-0,4876	0,1514	-0,2418	0,7036	0,5712	-0,4360	1,1023	-1,9063
BINT37P		0,1131	0,0837	0,1367	-0,6728	-1,0234	0,3774	-0,4217	0,8932	1,0168	0,0690	1,6944	-1,6167
COHAB	1,2240	0,5267	0,9540	0,9492						-0,5685	0,3327	0,4959	0,3276
MARRY	2,0481	1,4142	0,8689	0,9766						-1,6978	-0,0375	-0,6165	0,3633
TOTCOHAB	-0,0996	-0,0286	-0,0649	-0,0616			0,1056	-0,0887		0,0236	-0,1980	-0,1086	-0,0536
TOTMARRY	-0,1722	-0,1322	-0,1098	-0,1061					0,0234	0,1031	0,0939	0,0153	-0,0399
SCHOOL	-1,0411	-0,6767	0,0310	0,2511	-0,7216	-1,5310	-0,0880	-0,8329	0,9772			-2,6382	-0,3743
TOTSCHOOL	0,0043	0,0289	-0,0337	-0,0905	0,0987	0,1026	0,0725	0,0336	-0,0557	0,5650	-0,0095	0,2868	0,0170
WORK	-0,2688	-0,3145	-0,0996	0,0982	0,0705	-0,2080	-0,3611	0,0481	0,5128	-1,8401	1,4714		
TOTWORK	0,0398	0,0271	-0,0222	-0,0220	0,0094	0,0670	0,0493	-0,0076	-0,0199	0,0381	-0,2064	0,2034	-0,0151
LTREND	-0,3392	-0,1464	-0,6770	-0,9819	1,2988	-1,2446	0,4701	-1,3310	1,2987	0,6083	-0,4136	-0,1285	0,6542
PGDUR13					1,3905	2,0784	-1,4659	0,8663	-1,0788	-0,6338	0,5640	-0,5833	0,4477
PGDUR46					0,9930	3,3058	-0,9309	1,8914					
PGDUR79					1,3550	2,4216	-0,7692	1,2386					
PGDUR49									-1,0267	-2,3979	0,6731	-1,9925	2,5451

BELGIUM	FIRST	SECOND	THIRD	FOURTH+	SINCO	SINMAR	COSIN	COMAR	MARSIN	SSCH	ESCH	SWORK	EWORK
INTERCEPT	-4,4108	-12,3904	-12,7869	-11,1627	-26,8547	-24,3625	-12,4111	-0,4226	-7,2806		-22,7969	11,3469	-11,1314
PARITY1					2,0077	0,0116	-0,9954	-0,0878	-0,8275		-1,3723	-0,6944	1,0581
PARITY2									-0,9247		-2,4909	-0,6025	1,3875
PARITY2P					1,8591	0,1045	-2,1009	0,0900					
PARITY3P									-1,4485		-2,1639	-0,7741	1,3579
PARITY4				0,2087									
PARITY5P				0,3589									
AGE	0,2935	0,4354	0,2882	0,2949	0,8646	2,0880	-0,3203	-0,1033	-0,2320		1,5551	-0,9528	-0,1832
AGESQU	-0,0062	-0,0087	-0,0064	-0,0075	-0,0178	-0,0472	0,0052	0,0002	0,0017		-0,0326	0,0075	0,0043
BINT1324		1,1726	0,9359	0,6560	-1,3792	-0,7953	1,0766	-0,0656	0,3073		1,1941	-0,1536	-0,8791
BINT2536		1,0279	0,8002	-0,0002	-1,2183	-5,7592	0,7045	-0,2109	0,4460		2,2591	0,3419	-0,9495
BINT37P		0,5963	0,7838	0,0556	-1,3249	-1,0505	1,2324	0,0055	0,6260		1,1666	0,6651	-0,9561
COHAB	1,3194	2,4602	1,5584	-1,5150							0,7840	-0,1164	0,6352
MARRY	2,6829	2,7073	2,0762	0,6759							0,2975	-0,4752	0,4174
TOTCOHAB	-0,0074	-0,1252	-0,1468	0,1250			0,0252	-0,0914			-0,1789	0,0290	-0,1208
TOTMARRY	-0,1028	-0,1305	-0,2077	-0,0382					0,1232		-0,2229	0,0708	-0,0660
SCHOOL	-1,8758	-1,7961	0,1076	-4,8279	-1,7376	-3,2218	-1,4471	-0,6071	0,7499			-8,3443	1,5023
TOTSCHOOL	0,0264	0,1520	0,0744	0,0137	0,0646	0,1126	0,0305	0,1217	-0,0110			0,7353	-0,0836
WORK	-0,3650	-0,4464	-0,3779	-0,2969	-0,4119	-0,2915	-0,7727	-0,4712	-0,2255		9,8843		
TOTWORK	0,0457	0,0293	-0,0162	0,0181	0,0916	0,1797	-0,0086	0,0602	0,0018		-8,2449	0,5313	-0,1117
LTREND	-1,4279	-0,0417	0,9338	0,8754	2,9984	-0,8927	3,2421	-0,4457	1,4168		-0,0028	0,0309	2,4084
PGDUR13					0,8933	1,9546	-0,4120	1,2757	-2,1377		2,4742	-0,4811	0,4745
PGDUR46					1,0417	3,5883	-0,3197	2,2099					
PGDUR79					1,3637	3,0654	-4,6186	1,0201					
PGDUR49									-0,9506		1,7906	-1,1187	0,7366

ITALY	FIRST	SECOND	THIRD	FOURTH+	SINCO	SINMAR	COSIN	COMAR	MARSIN	SSCH	ESCH	SWORK	EWORK
INTERCEPT	-5,1470	-4,1729	-4,2725	4,5709	-16,9623	-15,2620	-17,7547	-0,5924	-13,2494		-6,4170	-3,4909	-6,3138
PARITY1					1,7894	0,1964	-6,5390	0,3623	-0,7945		-0,6180	-1,1573	0,1431
PARITY2									-1,1169		-0,8676	-1,4903	0,0059
PARITY2P					1,6440	-0,2834	-8,3913	-0,3609					
PARITY3P									-1,7202		-1,7637	-1,4350	-0,1688
PARITY4				0,4721									
PARITY5P				1,0519									
AGE	0,2186	0,0540	0,1169	-0,0157	0,2587	1,1443	0,1569	0,1880	-0,1001		0,1703	0,0713	-0,0392
AGESQU	-0,0041	-0,0014	-0,0030	-0,0015	-0,0049	-0,0218	-0,0022	-0,0046	0,0001		-0,0030	-0,0046	0,0000
BINT1324		0,5718	0,3515	0,0988	-6,1559	-1,4915	5,4182	-0,9107	0,0876		0,1256	0,1871	-0,3630
BINT2536		0,9185	0,5849	0,2804	-1,0952	-0,9888	5,3090	-0,6386	0,3905		0,0771	0,4553	-0,4202
BINT37P		1,1671	1,0245	0,5559	-0,9064	-1,9065	6,4892	-0,8483	0,4345		0,3780	0,8169	-0,4086
COHAB	2,9725	0,8217	2,0506	2,8880							-0,4203	0,3621	0,5200
MARRY	3,7782	1,8443	1,5280	1,0228							-0,2047	-0,4061	-0,1139
TOTCOHAB	-0,1297	0,0034	-0,1159	-0,2262			-0,0452	-0,0192			0,0244	-0,0421	-0,1348
TOTMARRY	-0,2435	-0,1454	-0,1546	-0,0732					0,0828		-0,0005	0,0021	0,0195
SCHOOL	-0,5982	-0,1235	-0,0392	-0,5543	-0,9214	-1,1862	0,9157	-0,2227	0,1652			-1,6723	0,3437
TOTSCHOOL	-0,0009	0,0125	0,0024	0,0270	0,0506	0,0255	-0,0707	0,0141	0,0227			0,1622	-0,0141
WORK	-0,3967	-0,3450	-0,0809	-0,9618	0,0635	-0,5357	-0,2878	-0,4356	0,4953		0,2657		
TOTWORK	-0,0008	-0,0248	-0,0159	0,0681	0,0506	0,0747	0,0220	0,0140	0,0066		-0,0432	0,2138	-0,0461
LTREND	-1,0911	-0,6282	-0,8110	-2,5184	1,7174	-1,1250	2,7684	-1,3711	2,1091		-0,1190	-0,0322	0,8088
PGDUR13					2,8399	3,1707	-6,6941	1,2120	-4,3950		0,4320	-0,6293	0,5707
PGDUR46					2,4385	3,7188	-6,7210	1,6662					
PGDUR79					2,1883	2,7694	-6,6875	1,2357					
PGDUR49									-0,6584		0,1268	-1,3753	0,6034

SPAIN	FIRST	SECOND	THIRD	FOURTH+	SINCO	SINMAR	COSIN	COMAR	MARSIN	SSCH	ESCH	SWORK	EWORK
INTERCEPT	-7,7547	-4,2104	1,0207	-1,0597	-22,1839	-21,6744	-10,3310	-1,0772	-6,1742	13,0996	-5,8204	0,2439	-7,2199
PARITY1					1,8592	1,5319	0,0371	0,1211	-0,6006	-1,3992	0,1647	-0,6903	0,2634
PARITY2									-1,0123	0,0433	-0,1848	-0,7443	0,1978
PARITY2P					1,7942	-0,1955	-0,5057	-0,2051					
PARITY3P									-0,2893	-4,8296	-0,2942	-0,7270	0,0572
PARITY4				-0,0848									
PARITY5P				0,7904									
AGE	0,2485	0,1971	0,1150	0,3396	0,4480	1,5185	-0,0150	0,0863	-0,2854	-1,8953	0,2976	-0,2335	-0,0565
AGESQU	-0,0050	-0,0036	-0,0026	-0,0072	-0,0087	-0,0305	0,0002	-0,0017	0,0024	0,0277	-0,0045	0,0013	0,0011
BINT1324		0,5001	0,3129	0,5914	-0,3945	-2,4056	0,8155	-0,6785	0,3757	1,2059	-0,0674	0,1655	-0,4355
BINT2536		0,9950	0,6692	0,1597	-0,8255	-2,2503	-0,2008	-1,3222	0,9229	1,7218	-0,5070	0,2796	-0,5736
BINT37P		1,2039	1,0485	0,3324	-0,3922	-2,6914	-0,0530	-0,7109	0,6272	2,2985	0,0784	0,8323	-0,3539
COHAB	2,4804	1,6644	1,7051	-3,1135						-0,5486	0,0954	0,2834	0,4933
MARRY	3,6440	2,4751	1,9198	1,8417						-0,2144	0,0601	-0,8296	0,2703
TOTCOHAB	-0,1771	-0,0203	0,0364	0,1268			0,0709	-0,1400		0,1217	-0,0286	-0,0893	-0,0801
TOTMARRY	-0,2356	-0,1271	-0,1549	-0,0365					0,1244	-0,1000	-0,0044	0,0101	-0,0458
SCHOOL	-0,9414	-0,5090	-0,0928	-1,5117	-1,0554	-1,5837	1,3149	-0,3555	0,3134			-2,0414	0,2851
TOTSCHOOL	-0,0438	0,0375	0,0454	0,0742	0,1198	0,0121	-0,0058	0,0230	0,0611	0,6068	-0,1002	0,2138	-0,0472
WORK	-0,4335	-0,4129	-0,4079	-0,1000	-0,3024	-1,3739	0,1307	-0,0697	0,5030	-1,6823	0,3619		
TOTWORK	0,0195	0,0015	0,0011	-0,0004	0,0510	0,1663	-0,0065	0,0192	0,0079	0,0558	-0,0437	0,2043	-0,0970
LTREND	-0,3827	-1,4057	-2,3901	-2,5697	2,6287	-0,4025	1,3963	-1,1183	0,9661	2,1393	-0,3547	0,0245	1,2232
PGDUR13					2,5226	3,0145	-0,8775	1,4426	-0,5339	-1,7079	0,4420	-0,6167	0,6606
PGDUR46					1,2687	4,0305	-0,4114	1,5771					
PGDUR79					-4,5703	2,8362	0,4673	0,9608					
PGDUR49									-0,7638	-1,8728	0,5690	-1,0018	0,8696

SWEDEN	FIRST	SECOND	THIRD	FOURTH+	SINCO	SINMAR	COSIN	COMAR	MARSIN	SSCH	ESCH	SWORK	EWORK
INTERCEPT	-7,9795	-14,5123	-18,0603	-11,0105	-11,9436	-13,5395	-8,5269	-2,3563	-6,1463	1,0509	-9,2853	-7,1525	-4,1491
PARITY1					0,6511	0,1487	-0,8405	0,5628	-1,1624	-3,1275	0,9017	-2,8383	2,1525
PARITY2									-1,6562	-2,8896	0,8784	-2,7612	2,1327
PARITY2P					0,6428	-0,0323	-1,1062	0,6274					
PARITY3P									-1,3252	-2,5858	0,8477	-2,4536	2,2051
PARITY4				0,3037									
PARITY5P				1,2448									
AGE	0,3541	0,3047	0,2992	0,1718	0,4895	1,0560	-0,0725	0,2028	-0,0755	-0,4127	0,5085	0,3554	-0,1485
AGESQU	-0,0061	-0,0066	-0,0059	-0,0050	-0,0106	-0,0177	0,0012	-0,0023	0,0005	0,0024	-0,0078	-0,0120	0,0024
BINT1324		1,1840	1,0280	1,1984	-0,9154	-1,2092	0,5662	-0,4349	0,4980	1,9304	-1,3290	1,8309	-2,1612
BINT2536		1,4524	1,2595	1,1844	-0,8916	-1,0617	0,9347	-0,6107	1,0644	2,7489	-1,0950	1,9589	-2,1058
BINT37P		1,0157	1,2812	1,1410	-0,5027	-0,9998	0,7382	-0,8015	1,0155	3,4604	-1,0426	2,7405	-2,0720
COHAB	1,9586	1,8902	2,1363	2,0744						-0,1531	0,0414	0,4021	-0,0841
MARRY	2,9842	2,3573	1,8929	0,9681						-0,3944	-0,3179	-0,3593	-0,1860
TOTCOHAB	-0,0141	-0,0357	-0,1327	-0,1336			-0,0167	-0,0181		-0,0034	-0,0173	-0,0351	-0,0199
TOTMARRY	-0,1802	-0,0849	-0,1056	-0,0260					0,0186	0,0084	0,0473	0,0652	-0,0066
SCHOOL	-0,6962	-0,7577	-0,7123	-0,2841	-0,7718	-1,5128	-0,1063	-0,8000	0,4587			-4,4075	1,4679
TOTSCHOOL	-0,0546	0,0634	0,0166	0,1043	0,0807	-0,0912	-0,0372	0,0339	-0,0050	0,3370	-0,0359	0,3438	-0,0209
WORK	0,1190	0,0125	-0,1199	-0,5201	0,0556	-0,9852	-0,2654	-0,1247	-0,0141	-4,0737	1,9608		
TOTWORK	-0,0224	0,0011	-0,0560	0,0003	0,0556	-0,1169	-0,0407	-0,0346	-0,0085	0,2419	-0,1412	0,3972	-0,0774
LTREND	-0,7930	1,2086	2,0878	0,9326	0,5343	-1,8093	1,4575	-1,6517	0,6009	0,7918	-0,2335	0,5692	0,9066
PGDUR13					1,8735	2,5651	-1,3073	1,0687	-2,1510	-0,8106	0,2927	-0,2323	-0,2393
PGDUR46					1,5850	2,7491	-1,2722	1,3784					
PGDUR79					1,7530	1,8941	-1,7799	0,6513					
PGDUR49									-1,5897	-2,9193	1,0995	-1,6507	1,2215

Appendix II – Microsimulation Projects

ASPEN	ASPEN is an agent based economics simulation model. It calculates the consequences of various legal, regulatory and policy changes. Agents in Aspen not only can communicate with one another but also make "real-life" decisions. Through use of evolutionary learning techniques, the agents adapt their behavior according to <u>changing economic conditions and past experience</u> .	Sandia National Laboratories USA	http://www-aspen.cs.sandia.gov
CORSIM	CORSIM, based at Cornell University, was begun in 1987 building up on the first dynamic microsimulation model DYNASIM and is now in its third generation. Built both to simultaneously support basic research into fundamental socioeconomic processes and as a platform for a broad range of policy analysis, the core CORSIM modules were also widely adapted by other models, including the Canadian DYNACAN and the Swedish SVERIGE model. Individual and family behavior is represented by approximately 1100 equations and 7000 parameters as well as dozens of algorithms. Typical applications include the estimation of welfare costs and the distribution of benefits of welfare reform of various US administrations.	Strategic Forecasting USA	http://www.strategicforecasting.com/
DMMS	The aim of the Darmstadt-Mikro-Makro model is the integration of a micro-model of the household sector into a macro-model. The focus of the analysis lies on the <u>interaction between both levels</u> .	TU-Darmstadt Germany	http://www.bwl.tu-darmstadt.de/vwl4/forsch/projekte/pt_liste.htm
DESTINIE	Computes social security contributions, benefits and taxes since 1945, and simulates the socioeconomic evolution of a microsimulation population till 2040, relying on existing demographic and economic projections. Within this relatively long interval, DESTINIE allows to compute the rate of return of public pensions for different <u>generations born between 1920 and 1974</u> .	INSEE France	http://www.insee.fr
DYNACAN	The focus lies on generating longitudinal projections of the Canada Pension Plan (CPP).	Canada	http://www.hrdc-drhc.gc.ca/
DYNAMOD	DYNAMOD is a dynamic microsimulation model of the Australian population which is designed to project characteristics of the population over a period of up to 50 years. Major elements of the model include demographics, international migration, <u>education, the labour market and earnings</u> .	NATSEM Australia	http://www.natsem.canberra.edu.au
DYNASIM	The Dynasim model was the first dynamic microsimulation model. It was developed by Orcutt between 1969 and 1976. Its successor DYNASIM2 includes family formation, geographic mobility, education, disability pensions, labor force <u>participation, labor market earnings, taxes and transfers</u> .	The Urban Institute USA	http://www.urban.org/
EUROMOD	EUROMOD is a static 15-country Europe-wide benefit-tax model that concerns with the distributional impact of changes to personal tax and transfer policy.	University of Cambridge UK/EU	http://www.econ.cam.ac.uk/dae/mu/euomod.htm
LOTTE	Lotte is a static tax model that is used in budget work by the Ministry of Finance and the Parliament.	Statistics Norway	http://www.ssb.no/
MOSART	The MOSART model projects the Norwegian population and its characteristics. This includes analysis about the population size and composition and the consequences for <u>the educational level, labor supply and public pension</u> .	Statistics Norway	http://www.ssb.no/
NATSEM STINMOD- STATAX	The STINMOD distributional model simulates the impact of major federal government activities such as cash transfers, income tax and the Medicare levy on individuals and families in Australia. STINMOD can be used to analyze the <u>distributional and fiscal impact of both current and new policies</u> .	NATSEM Australia	http://www.natsem.canberra.edu.au/index.html
POLIMOD	The POLOMOD model concerns with the distribution of income and the effect of changes in personal tax and social security policy on distribution.	University of Cambridge UK	http://www.econ.cam.ac.uk/dae/mu/polimod.htm
SESIM	SESIM is used to evaluate the long term effects of the Swedish national system of study allowances	Swedish Ministry of Finance	http://www.sesim.org/
SF3	SF3 model consists of three versions namely one cross-sectional, one longitudinal one and one static model. The cross-sectional is recursive and comprises demographic events, household formation, education, labor supply, income, taxes, transfers, <u>consumption, saving and wealth</u> .	Germany	
SPSD	The SPSPD is a tool for analyzing the financial interactions of government activities and individuals.	Statistics Canada	http://www.statcan.ca/english/spspd/
SVERIGE	SVERIGE is a spatial microsimulation model used to evaluate the spatial consequences of various public policies. It is based on a database of the whole Swedish population.	Spatial Modelling Centre Sweden	http://www.smc.kiruna.se
XECON	XEcon (for eXperimental Economy) is a dynamic microsimulation model of an agent-based economy populated with bounded rational individuals and firms.	Statistics Canada	http://www.statcan.ca/english/spspd/

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